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The Dynamic Prediction of Company Failure

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Abstract. Across disciplines, and particularly in medicine, Cox's proportional hazards model is one of the most popular models for analyzing survival. We use a Cox model with dynamic variables to estimate survival probabilities and make dynamic financial distress predictions for a large sample of Australian listed companies. This is one of relatively few studies to apply dynamic variables in forecasting financial distress. It is the first study to provide forecasts of survival probabilities using the Cox model with dynamic variables. In contrast to most bankruptcy studies using static models, our model's predictive accuracy improves as the time horizon lengthens.

JEL Classification: C41, G14, G32, G33

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1. Introduction

Much of the previous work in financial distress prediction focuses on static predictions and uses static variables in estimating the predictive model. In this study our goal is to make dynamic predictions, and to use dynamic variables in estimating the model. With dynamic predictions we allow the probability of financial distress to vary over the forecast period. With dynamic variables the model estimation allows for changes in the financial characteristics of a firm over time.

The motivation for the paper is threefold. First dynamic forecasts of the probability vector for failure f_t to f_{t+n} (where f_t is the probability of failure at time t) have been much less explored than the static forecast of a single failure probability f. Second relatively little use has been made of dynamic forecasting variables. In most applications including a data vector of say the last five years profitability in forming a forecast requires five separate profitability variables in the model and this is not commonly done.[1] In the approach that we use the vector of data is represented by a single profitability variable. Third, one of the most popular techniques for survival analysis is Cox regression, Cox (1972). Unfortunately, for reasons we discuss later, forming forecasts is problematic when a Cox regression contains dynamic variables. We implement a procedure that overcomes this problem.

The work on estimating models which allows for time varying probabilities of financial distress began in the mid 1980s (see for example Crapp and Stevenson, 1987). These models use the techniques of survival analysis, and have attracted increasing attention following the dynamic model of Shumway (2001). Despite the growing use of

[1] A more common approach, as exemplified by Altman (1968,) is to estimate five separate models using data one year before the failure, two years before the failure and so on back to year five.

survival analysis in modeling financial distress, relatively little attention has been given to the use of dynamic variables in estimating these models. Initially this was because of computational difficulties in estimating models with time-varying (dynamic) variables, and even when this problem was overcome a problem remained in making forecasts when using the Cox regression model.

A key element in forecasts using the Cox regression model is the baseline hazard. In making a forecast the baseline hazard is scaled up, or down, according to the firm's risk factors and this scaled hazard is used to compute the probability of financial distress. When time-varying variables are introduced into the Cox model, forming estimates of the baseline hazard has been problematic. Consequently making forecasts have also been problematic with time varying variables.

Cox's model has had considerable use in medical studies. Chen et al. (2005) apply the Cox model with time-varying variables to find the effect of biochemical covariates on death attributed to liver cancer. They implement a method for estimating the baseline hazard and hence are able to make survival forecasts with time-varying variables. Chen et al. also published the code for implementation of these estimation procedures in SAS. Following the approach of Chen et al., we construct a time-dependent Cox's regression model for the prediction of financial distress.

Using firm specific data on Australian Securities Exchange (ASX) listed firms from 1989 to 2006; a time-dependent Cox's regression model is developed with seven predictor variables measuring profitability, leverage (book and market), liquidity, cash flow, size, and growth opportunities. Each variable captures the impact of fourteen years of data for firms that are in the estimation sample for the full fourteen years. Book leverage, cash flow generating ability and market leverage are found to be significant predictors of financial distress. Receiver operating characteristic (ROC) curves show that the model has modest predictive power and unlike most bankruptcy models the performance of the model improves as the forecast period lengthens.

The remainder of this paper is set out as follows. Section 2 reviews the literature in the area of bankruptcy prediction, introduces survival analysis, discusses Chen et al. (2005) and explains how predictive accuracy is evaluated. Section 3 presents the methodology to construct a Cox's regression model with time-varying variables. Section 4 describes the data. Section 5 presents the results of parameter estimates followed by assessment of predictive accuracy of the model. Section 6 concludes the paper and offers some possible future research directions.

2. Bankruptcy Prediction Literature

EARLY BANKRUPTCY PREDICTION STUDIES

Research on bankruptcy prediction has been of substantial interest to accounting and finance academics and practitioners for the last four decades. A number of empirical approaches have been applied to the bankruptcy prediction problem since the pioneering work of financial predictive modeling by Beaver (1966), Altman (1968) and Ohlson (1980). The initial approach to predicting corporate bankruptcy has been to apply a statistical classification technique to a set of samples containing both bankrupt and non-bankrupt firms. The principal tools for the early studies have been multivariate discriminant analysis (Altman, 1968) and logit analysis (Ohlson, 1980). The task of predicting bankruptcy of a firm can be posed as a classification problem: given a set of classes (for example, bankrupt and non-bankrupt) and a set of input data vectors, the task is to assign each input data vector to one of the classes. Since the 1980s, the literature has progressed to non-parametric approaches such as recursive partitioning algorithms (Frydman et al., 1985), neural networks techniques (Odom and Sharda, 1990; Coats and Fant, 1992; Tam and Kiang, 1992; Wilson and Sharda, 1994) and survival analysis (Lane, Looney and Wansley, 1986; Crapp and Stevenson, 1987; Chen and Lee, 1993; Bandopadhyaya, 1994).

SURVIVAL ANALYSIS

In recent studies of financial distress (bankruptcy) prediction, the need to take the time dimension into account is increasingly being recognized. LeClere (2000) points out that qualitative response models such as logistic regression or probit models employ data from the time period directly preceding the occurrence of the event of bankruptcy. Hence, the model is static in that it ignores the entire time period preceding the event. Furthermore, the information provided by the estimated model is limiting as the data used to estimate the probability of financial bankruptcy may only be available immediately prior to the event. Shumway (2001) also points out the discordance between single-period bankruptcy prediction models and multiple-period bankruptcy data. He argues that the single-period classification models that have been commonly used for predicting bankruptcy yield biased and inconsistent estimates because they ignore the fact that the characteristics of firms change through time. Liu (2004) also observes that failure rates change with changes in the time-series of economic data.

Survival analysis is ideally suited to introducing a time dimension into financial distress prediction since the objective is to estimate $S(t) = P(T > t)$, the probability that financial distress will occur at a time *T* which lies beyond the time horizon *t*, for a range of values of *t*. Thus, a time dimension is embedded in the dependent variable of the model. It is also possible to introduce a time dimension into the independent variables by making them time-varying. Thus, for example, a vector of ratios giving the return on assets for a firm over a ten year period would be treated as a single variable, but the value of that variable would be updated as we follow the firm through time in estimating the survival model. The problem with time-varying variables in the past has been in forming forecasts. Previous studies (e.g., Wheelock and Wilson, 1995; Kim et al., 1995) have not reported the baseline hazard estimates since estimates of the baseline hazard are difficult to obtain when covariates in the model are time-varying. Recent advances, however, have made this somewhat less difficult.

Chen et al. (2005) estimate a time-dependent Cox's regression model for deaths from liver cancer. Using a method from Anderson (1992), they estimate the integrated baseline hazard. Two SAS Macro programs for time-dependent Cox's regression are introduced in Chen et al. The first program is for parameter estimates on risk factors, deriving the baseline hazard and the prediction of survival on the basis of time-dependent covariates. The second program is for model validation using receiver operating characteristic (ROC) curves. We use the SAS Macro programs in Chen et al., with some modifications, to estimate our financial distress models.

EVALUATION OF PREDICTIVE ACCURACY

To assess the predictive accuracy of the models, we use the survival probabilities to classify each firm as failing or surviving, and then compare the classification with the actual outcome. Two questions arise in this process. First, which of the probabilities to select from the time profile and, second, what value to choose as a cut-off value to convert from a probability to the state forecast of failing or surviving. These are difficult issues to address.

As Pacey and Pham (1990) point out, assessments of the accuracy of financial distress models are often misleading because of (i) the use of arbitrary cut-off points; and (ii) the assumption of equal costs of errors in prediction tests. The suggested corrective measures are as follows: (i) derive the optimal cut-off point based on minimizing the costs of misclassification; and (ii) define the cost of Type I and Type II errors explicitly.

Setting an optimal cut-off value requires knowledge of the costs of Type I and type II errors in the specific decision context. Given the greater seriousness of classifying a financially distressed firm as not financially distressed, it is assumed that the misclassification cost for such Type I Errors is far higher than that of Type II Errors (Altman et al., 1977). Based on this assumption, some researchers have attempted to draw an optimal cut-off point that yields the lowest Type I Error (Koh, 1992; Tan and Dihardjo, 2001). However, non-failing firms are in the overwhelming majority. Consequently, as Pacey and Pham (1990) show even a small Type II error rate with a small cost per error is likely to lead to a large error cost in total because so many firms are involved.

Optimizing the cut-off probability therefore requires a clear understanding of the likely total cost of Type I and Type II errors. However, establishing what these costs might be is a difficult exercise. As will be shown in Section 5.2, the use of ROC curves to evaluate predictive accuracy avoids the need to address the cut-off problem since all possible cut-off probabilities are considered.

3. Time-dependent Cox's regression model

In Cox's model the survival probabilities are obtained from a model of the hazard rate. The hazard rate is the rate of change in the probability that an event will occur in an interval of time, given survival until the start of that interval. Cox's hazards model with time-dependent covariates can be expressed as:

$$h_i(t \mid z(t)) = h_0(t) \cdot \exp\left\{ \sum_{j=1}^{p} \beta_j z_j^i(t) \right\}. \tag{1}$$

$h_i(t \mid z(t))$ is the time-dependent hazard function for firm *i* at time *t*. $z_j^i(t)$ denotes the value of the *j*th covariate at time *t* for the *i*th firm, β_j is the corresponding coefficient for z_j^i, while $h_0(t)$ is the baseline hazard representing the effect of duration on the hazard in the absence of covariates. Thus, the hazard at time *t* depends on the value of predictor variables at time *t*.

In most of the previous bankruptcy literature, each annual observation of firms has been treated as an independent observation and so researchers could not take advantage of all the available multiple-year financial information. Using Equation (1), we are able to "exploit each firm's time-series data by including annual observations as time-varying covariates" (Shumway 2001: p.102). That is, if a firm has been observed for twelve years in the set of firms potentially at risk of financial distress, the values of each covariate, $z_j^i(t)$, for that firm are to be updated twelve times from year to year (*t*). Consequently, we are able to retain multiple-year time-series data for each firm according to its life time (or duration) and make use of all the data within the periods to estimate the regression coefficients.

In a time-dependent model, the value of covariates, $z_j^i(t)$, changes with time, and therefore, the hazard ratio (*HR*) also varies with time and is defined as follows.[2]

$$HR(t \mid z(t)) = \frac{h_i(t \mid z(t))}{h_0(t)} = \exp\left\{\sum_{j=1}^{p} \beta_j z_j^i(t)\right\}. \qquad (2)$$

PARTIAL LIKELIHOOD FUNCTION

It is helpful to introduce some concepts in survival analysis in order to understand the estimation of the model. First, the risk set, *R(t)*, is defined as the set of firms (individuals) which are observed at risk of event at time *t*. Firms are said to enter the risk set when they become at risk of experiencing the event and leave the risk set either when they are censored or when the event occurs to them (fail or become financially distressed). Being censored means that a firm leaves the risk set for some other reason than experiencing the event, for example the firm may be taken over, or may still survive at the termination of the study.

Second, it is important to distinguish between calendar time and event time. A graphical demonstration of the difference between calendar time and event time is presented in Figure 1. An event time approach looks to the duration (time spent in the risk set) of a firm and sorts observations according to their duration on study. The event time approach is used in our study as is commonly the case in other survival analysis studies.

[Figure 1 about here]

[2] When there are no time-varying variables the ratio of hazards for any two firms is constant over time and so traditionally the model has been known as Cox's proportional hazards model.

After constructing the risk set at each event time, it is possible to estimate the likelihood of a firm's failure. The probability that firm *i* fails at time *t*, conditional upon it having survived up until time *t*, is the ratio of the hazard rate of firm *i* to the sum of the hazard rates of all firms in the risk set for each time *t*:

$$L_i = \frac{h_i(t \mid z(t))}{\sum_{k \in R_i(t)} h_k(t \mid z(t))} = \frac{h_0(t) \cdot \exp\left\{\sum_{j=1}^{p} \beta_j z_j^i(t)\right\}}{\sum_{k \in R_i(t)} h_0(t) \cdot \exp\left\{\sum_{j=1}^{p} \beta_j z_j^k(t)\right\}} = \frac{\exp\left\{\sum_{j=1}^{p} \beta_j z_j^i(t)\right\}}{\sum_{k \in R_i(t)} \exp\left\{\sum_{j=1}^{p} \beta_j z_j^k(t)\right\}}. \qquad (3)$$

The baseline hazard cancels in the numerator and denominator, and so the exact times of each failure are irrelevant, only the order of events is required.[3]

Given L_i, the partial likelihood function, with the incorporation of time-varying covariates, can then be obtained by taking the product of the probabilities across all observed failures, *m*, such that:

$$PL = \prod_{i=1}^{m} L_i = \prod_{i=1}^{m} \left[\frac{\exp\left(\sum_{j=1}^{p} \beta_j z_j^i(t)\right)}{\sum_{k \in R_i(t)} \exp\left(\sum_{j=1}^{p} \beta_j z_j^k(t)\right)} \right], \qquad (4)$$

where *i* is the firm in the event of failure and *k* is the firm in the risk set at time *t*. The coefficient estimation process implies that the time-varying covariate values of every firm in the risk set should be recorded and measured at each 'failure time'. However, in practice, it is highly unlikely to have the complete covariate measures for all firms at each point in time because the data set is likely to have missing observations, especially for

[3] The estimation procedure has to be modified where more than one event occurs at the same time. In the present study, the Breslow method of handling tied data is used.This is the default method and is appropriate when ties are relatively few.

financially distressed firms. Figure 2 illustrates the arrangement of the data in forming the likelihood function of Equation (4).

[Figure 2 about here]

INTEGRATED BASELINE HAZARD

To generate survival probabilities at each time t, we need to estimate the baseline hazard function, $h_0(t)$. We follow the approach of Chen et al. (2005), which estimates the integrated baseline hazard function following the equation of Cox's proportional hazards model with time-dependent covariates from Andersen (1992). The integrated baseline hazard function $\hat{H}_0(t)$ can be estimated as follows.

$$\hat{H}_0(t) = \sum_{\tilde{T}_i \le t} \frac{D_i}{\sum_{j \in R(\tilde{T}_i)} \exp\left(\hat{\beta}' \cdot z_j\left(\tilde{T}_i\right)\right)} . \tag{5}$$

D_i is the indicator for whether the firm i experiences the failure, $\tilde{T}_i$ is the failure time for the ith firm, $\hat{\beta}$ is the vector of estimated coefficients, and $z_j\left(\tilde{T}_i\right)$ is the value of the jth covariate at the failure time of the ith firm.

The integrated baseline hazard function $H_0(t)$ can also be written as:

$$H_0(t) = \sum_{t_i \in t} \left[h_0(t_{m-1}) \times (t_m - t_{m-1})\right], \tag{6}$$

where $H_0(t)$ is a step function, which is discontinuous at t_m. This allows the baseline hazard $h_0(t)$ to be derived from the integrated hazard.

Using the estimated baseline hazard rate, $\hat{h}_0(t)$, computed from equations (5) and (6), the estimated hazard rate of firm i with covariates $z_i(t)$ at time t is derived as:

$$\hat{h}_i(t) = \hat{h}_0(t) \times \exp\left(\hat{\beta} \cdot z_i(t)\right). \tag{7}$$

It is noted that a time-dependent 'risk score' is defined as $\left(\hat{\beta} \cdot z_i(t)\right)$. The dynamic changes of the risk score over the time horizon studied and the corresponding survival probabilities will be presented in Section 5.

4. Data

SAMPLE SELECTION

Our sample includes publicly listed companies on the Australian Securities Exchange (ASX) from 1989 to 2006. Firms which are in the financial sector, as indicated by their GICS code, are excluded from the sample. We obtain annual accounting data from FinAnalysis and annual market capitalization data from Datastream. There are 1,716 non-financial firms with available accounting and market capitalization data.

We have 1,596 non-failed firms and 120 failed firms in our sample. Following the approach of Jones and Hensher (2004), firms are classified as "failed" if (i) they were delisted due to the failure to pay their annual listing fee to the ASX, or (ii) there was the appointment of liquidators, insolvency administrators, or receivers. We note that these are failure events that happen at specific dates, but there may be varying lags between the failure event and the onset of financial distress. We do not have the data to model these lags, but the advantage of dynamic probability forecasts, which give a trajectory to failure, lies in the potential for early warning of problems as the trajectory changes.

We collect annual accounting and market capitalization data for each company. The data contains yearly observations of financial performance for each company in the sample from 1989 through 2006. In total, we have 13,505 firm-year observations. Table I shows the number of failed and non-failed firms for each year over the sample period of 1989–2006. There are no failed firms between 1989 and 1993 and the sample sizes are small for 1989 to 1991. It may be that data on firms failing in this period has been deleted from our data sources and, if so, there is a survival bias problem here.

[Table I about here]

There are several extreme values among the variables observed. Following the approach of Shumway (2001), all values lower than the first percentile of each variable are set to that value, and analogous treatment is applied to all observations higher than the ninety-ninth percentile of each variable. The data after truncation is described in detail in Section 4.3.

The entire sample period (1989–2006) is divided into two separate samples, an estimation sample (1989–2002) and a holdout sample (2003–2006) for tests of predictive accuracy.

PREDICTOR VARIABLES

Key predictors of financial distress were identified from previous bankruptcy studies, and we focus on variables used in the recent major studies by Sobehart and Stein (2000), Shumway (2001), and Campbell et al. (2005). As this study is being conducted using Australian data, we also include some of the variables found to be useful in Australian studies by Castagna and Matolscy (1981), Jones and Hensher (2004) and Gharghori, Chan and Faff (2006).

A set of fundamental accounting-based and market-based variables initially considered is shown in Table II.

[Table II about here]

The accounting-based variables reflect measures of profitability (Net Income/Total Assets (NI/TA)), operating liquidity (Working Capital/Total Assets (WC/TA)), book leverage (Total Liabilities/Total Assets (TL/TA)) and cash flow generating ability (Net Cash Flow from Operations/Total Assets (CF/TA)). As a group, these ratios capture the strength of the firm's financial position.

Shumway (2001)'s and Campbell et al. (2005)'s market-based variables are also used in model estimation. The market-to-book (MB) ratio is commonly used as a proxy for growth opportunities (Rajan and Zingales, 1995; Baker and Wurgler, 2002; Faulkender and Petersen, 2005). Campbell et al. (2005) demonstrate that MB has a positive effect on the risk of failure "when market value is unusually high relative to book value" (p.11). Following Shumway (2001) the size measure we use is the value of the company relative to the value of all companies listed on the ASX. We measure this variable as Log(Firm Market Capitalization $_{i,t}$/Total ASX Market Value $_{t}$), which is denoted as RSIZE. Market Capitalization/Total Liabilities (MC/TL) is used as a measure of market leverage. Bigger values of this variable represent lower levels of leverage and it is expected that this variable will have a negative relationship with the risk of failure.

Shumway (2001) includes firms' past excess returns and stock returns volatility in the covariate set. However these two market variables are excluded from our model as there is insufficient data on failed observations. There are only twenty four failed observations with sufficient data in Datastream to compute excess returns and volatility.

SUMMARY STATISTICS

Table III presents descriptive statistics for annual observations of the predictor variables after the data filtering process described in Section 4.1. The minimum and maximum values reported in the table are calculated after truncation. The financial characteristics of non-failed firms are a noticeable contrast to those of failed firms for most variables.[4] For example, failed firms are found to have lower levels of profitability, operating liquidity and cash flow compared to those of non-failed firms. Meanwhile, non-failed firms have a lower level of book leverage and a higher market-to-book ratio. The dispersion of financial ratios among failed firms is also wider than that of non-failed firms, evidenced by higher standard deviations.

[Table III about here]

The first panel shows descriptive statistics for all firm-year observations of the entire sample and the other two panels report descriptive statistics for the estimation and holdout sample. For the whole sample we have 1,716 non-financial firms' information where 13,505 firm-year observations are obtained with 120 failure events. The second panel shows summary statistics for all firm-year observations of the estimation sample. There are a total of 1,278 firms and 8,815 firm-year observations in the estimation sample, of which 80 are failure events. For the holdout sample as shown in the third panel, we have 1,471 firms' information with 4,690 firm-year observations, where there are 40 failure events.

Table III shows that on average profitability (NI/TA) was negative for the full sample, the estimation sample, and the holdout sample. This is not the result of poor profits in a

[4] Wilcoxon-Mann-Whitney test is carried out for each variable to test the significance of differences of firm characteristics between failed and non-failed groups. The test shows the differences are statistically significant at the 1% level for all variables except for the WC/TA for the entire sample and the estimation sample, and at the 5% level for all variables, with the exception of WC/TA, for the holdout sample.

specific period. Panel D in Table III, shows that profitability, on average, has been negative in sixteen of the eighteen years studied. This result is surprising, but it is driven by small firms. The value weighted mean for NI/TA (not reported here) is positive. As shown in Panel E of Table III, if we restrict our sample to the top quartile of firms by size, the mean and median profitability are positive. If we limit the sample to the top half of firms by size, the mean is negative but the median is positive.

It is noted that not all public firms have complete accounting and market information available for estimating the parameters of the model. In this study, any firm-year observations with incomplete data were eliminated from the final sample. Table III, therefore only contains statistics for variables where all values are non-missing. The elimination of missing value cases was done for two reasons. First, handling missing values causes substantial computational problems and second including missing value cases is likely to lead to informative censoring as we discuss below.

In relation to defaulting firms Sobehart and Stein (2000) state, "…financial and market information are less likely to be complete or reliable in the time period leading up to default" (p.12). Thus missing data may be an indicator of failure.

We compare cases with missing and non-missing values using the Mann-Whitney test. The result shows that the missing data is associated with firms that have more negative profits, higher leverage, and more negative cash flow. It appears that the cases with missing data are financially weaker than firms with complete data and therefore are more likely to fail.[5] If this is true, and these firms were included in the study at the times when there was data and then treated as censored when data was not available, this would give

[5] We note, however, that we did not find any information that these firms were liquidated, went into receivership, or were delisted for failure to pay fees.

rise to informative censoring. That is, the censoring substitutes for the failure event and this violates the assumptions underlying the analysis.

Correlation matrices of the seven covariates in the model are constructed for the entire sample, the estimation sample and the holdout sample, respectively. The Pearson Product-Moment correlations are presented in Table IV. All of the correlations are statistically significant at the 1% level, but the correlations are not so large as to cause concerns about colliniarity. The highest correlation at about 0.65 is between Net Income/Total Assets and Net Operating Cash Flow/Total Assets.

[Table IV about here]

5. Empirical Analysis

MODEL ESTIMATION

The time-dependent Cox's regression model for the hazard has been estimated using the estimation sample (1989–2002) of 1,278 firms, with 80 failure observations. Panel A in Table V shows the total number of firms used in estimating the model parameters, and each number of failed and censored firms. The resulting coefficient estimates of the model are shown in Panel B in Table V, with their expected signs and their respective chi-square, and p-values.

[Table V about here]

From Panel B in Table V we see that all of the variables have coefficients of the sign expected and three of the variables are statistically significant in explaining failure risk. Higher book leverage, less cash flow generating ability, and lower MC/TL increase the probability of failure as expected. RSIZE, which was a significant predictor in previous studies (Shumway, 2001; Campbell et al., 2005) turns out to be not significant in this model. However, RSIZE is the only significant variable in the (unreported) model with untruncated data.

Table VI shows the changes of risk scores and survival probabilities by time horizon. The time-dependent risk scores can be calculated for each firm as $\hat{\beta} z_i(t)$. Following the approach of Chen et al. (2005), $\hat{\beta}$ is a vector of estimated coefficients shown in Table V and $z_i(t)$ is a vector of values of covariates for firm *i* at time *t*. For example, the risk score of Firm 1 at time 2 is estimated using the estimated coefficients from Table V and the values of seven predictor variables for firm 1 at the second year of the firm's life time.

The survival probabilities are calculated using Equation (7) and taking the exponential of the negative integrated hazard.

Panel A in Table VI presents the resulting risk scores and survival probabilities for ten randomly selected firms in the non-failed group and Panel B shows those for ten firms in the failed group.[6] Comparing these survival probabilities for the failed firms with the those for the surviving firms at the same time horizons (Lifetime), the failing firms have lower probabilities in all cases except for the comparison at 14 years. However, in most cases the differences are not great and the survival probabilities for the failed firms are generally high, with several above 0.9.

The explanation for the foregoing seems to lie in the interaction between the risk score and the baseline hazard. Since the incidence of failure in the estimation sample is small, the risk of failure for an average firm is small. Consequently, although the baseline hazard rises through time, it remains small. Thus, to obtain a small probability of survival

[6] Risk scores and survival probabilities are presented for only twenty firms in our study sample due to limited space.

requires a substantial scaling up of the baseline hazard by the risk score. It appears in this analysis that the risk scores for failed firms are not often large enough to achieve the required scaling up.

[Table VI about here]

MODEL VALIDATION

We now evaluate the ability of our time-dependent hazards model to predict failures. As discussed in Section 2, when the probability prediction is converted to a state prediction, picking the optimal cut-off value becomes an issue. Using ROC curves is one way to sidestep the problem of determining an optimal cut-off point, since it examines the predictive power of the model across the entire spectrum of possible cut-off points. The ROC curve for a particular model is determined by the hit rate (correctly predicting failures) and the false alarm rate (incorrectly predicting non-failures to failures). The ROC curves plot the combinations of the false alarm rate (X-axis) and hit rate (Y-axis) as the cut-off point is varied across all possible values. A detailed explanation of the ROC curve can be found in Hanley and McNeil (1982), Mason and Graham (1999), Sobehart and Keenan (2001), and Wong et al. (2007).

We form ROC curves at one-year intervals through time for both the estimation sample and the holdout sample. Table VII shows the area under the ROC (AUROC) curve of the in-sample and out-of-sample survival functions. The AUROC measures the predictive accuracy of the model and the higher the AUROC, the better the model's prediction. Predictions made at random have an AUROC of 0.5 and models that do not beat this benchmark have no predictive power.

[Table VII about here]

For in-sample estimates (see Panel A in Table VII), the time-dependent hazards model appears to perform better than a randomly allocated prediction with the exception of 1-year (0.4612) and 2-year (0.4887) horizon. The poor performance at these short horizons is because there were no failures in the estimation sample within this period. Interestingly, the model's estimates become better at longer horizons. For those firms that have been in the risk set for 14 years, our model has an accuracy of 81% in sample. This result is in direct contrast to most bankruptcy studies, where predictive accuracy deteriorates sharply as the time horizon lengthens. The model also has predictive accuracy out of sample (see Panel B in Table VII), but the time horizon is much shorter due to the much shorter time period covered by the holdout sample. Predictive accuracy improves from year 1 to year 3 but falls in year 4.

While the model has some predictive power, there is plenty of scope for improvement. It is possible that there is a problem with untimely or less than reliable financial statement information, especially for those firms approaching financial distress. It may, therefore, be worthwhile to include more market-driven variables such as past stock returns, and stock returns volatility which can be observed more frequently than accounting data. The current model does not allow for changes in macroeconomic variables, so a possible extension is to introduce such variables, or alternatively control for the effect of such variables by estimating the model in calendar time rather than event time. There may also be problems arising from survival bias, and this may be more prevalent in the early years of the study.

6. Summary and conclusions

Problems of time-varying predictor variables and baseline hazard estimates have been major obstacles to the application of survival analysis into multiple-period bankruptcy data. This study has taken a step towards solving these problems by applying the time-dependent Cox's regression model to Australian financial distress prediction. We use seven covariates, whose values are updated on a year by year basis from 1989 to 2006. The attractive feature of time-dependent survival modeling is that it allows for dynamic changes of firm's risk levels and its corresponding survival probabilities through time.

The results show that firms with higher book leverage, less cash flow generating ability and less market value relative to debt are more likely to fail, which is partly in line with the results found in Shumway (2001). However, the baseline hazard appears to have a strong effect on the estimated hazard rates relative to the risk factors for failing firms. An intriguing result in the study is the improvement in the accuracy of the financial distress probabilities as the time horizon lengthens. However, the predictive power of the model is modest and there is scope for considerable improvement.

Suggestions for future research include extending the model to incorporate more timely market information such as stock return and volatility, and to include variables that capture macroeconomic changes through time.

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Table I
Data sample

This table shows the total number of firms in our study sample, the number of non-failed firms, the number of failed firms and percentages of failed to non-failed firms for every year over the sample period of 1989 – 2006. Our study sample includes financially distressed (failed) firm data of publicly traded companies on the Australian Securities Exchange (ASX) between 1989 and 2006. Firms which are in the financial sector, as indicated by their GICS code, are excluded from the sample. There are 1,716 non-financial firms and 120 failed firms in our study sample. In total, we have 13,505 firm-year observations.

Year	No of firms	No of non-failed firms	No of failed firms	Percentage of failed to non-failed firms
1989	56	56	0	0.00%
1990	67	67	0	0.00%
1991	99	99	0	0.00%
1992	462	462	0	0.00%
1993	520	520	0	0.00%
1994	622	621	1	0.16%
1995	678	675	3	0.44%
1996	735	730	5	0.68%
1997	779	767	12	1.56%
1998	812	806	6	0.74%
1999	877	867	10	1.15%
2000	999	979	20	2.04%
2001	1,044	1,037	7	0.68%
2002	1,065	1,049	16	1.53%
2003	1,072	1,064	8	0.75%
2004	1,137	1,124	13	1.16%
2005	1,224	1,210	14	1.16%
2006	1,257	1,252	5	0.40%

Table II
Predictor variables used in previous bankruptcy studies

This table shows predictor variables used in a number of previous bankruptcy studies in the USA and Australia. We take into consideration those found to be useful from the recent major studies by Sobehart and Stein (2000), Shumway (2001), and Campbell et al. (2005). As this study is being conducted using Australian data, we also include some of the variables found to be useful in Australian studies by Castagna and Matolscy (1981), Jones and Hensher (2004) and Gharghori et al. (2006). Nine predictor variables are initially considered measuring profitability, leverage (book and market), liquidity, cash flow generating ability, size and growth opportunity, excess return and market sensitivity. Two market variables, firm's past excess return and price volatility, are excluded in our model as there is insufficient data on failed observations.

Description	Ratio / Variable	Abbreviation	Source	Frequency	Included in the present study
Accounting-based Variables					
Return on Assets (Profitability)	Net Income / Total Assets	NI / TA	Shumway (2001) Sobehart (2000)	Annual	Yes
Operating Liquidity	Working Capital / Total Assets	WC / TA	Castagna (1981) Gharghori (2006) Sobehart (2000)	Annual	Yes
Leverage	Total Liabilities / Total Assets	TL / TA	Gharghori (2006) Shumway (2001)	Annual	Yes
Cash flow generating ability	Net Cash Flow from Operations / Total Assets	CF / TA	Jones (2004)	Annual	Yes
Market-based Variables					
Market-to-Book Ratio	Market Capitalization / Total Equity	MB	Campbell (2005) Gharghori (2006)	Annual	Yes
Firm Relative Size	Log (Firm Market Capitalization $_{i,t}$ / Total ASX Market Value $_t$)	RSIZE	Campbell (2005) Shumway (2001)	Annual	Yes
Market Leverage	Market Capitalization / Total Liabilities	MC / TL	Gharghori (2006) Altman (1968)	Annual	Yes
Firm's Past Excess Return	$r_{i,t-1} - r_{m,t-1}$	EXRETURN	Campbell (2005) Shumway (2001)	Annual	No
Market Sensitivity	Stock Returns Volatility	SIGMA	Campbell (2005) Shumway (2001)	Annual	No

Table III
Descriptive statistics

This table shows descriptive statistics for firm-year observations of the ASX listed firms. Each firm has multiple observations according to firm age (duration). The data is reported after truncation of the top and bottom one percent of the distribution for each variable. NI/TA is the firm's net income divided by its total assets; WC/TA is the firm's working capital divided by its total assets; TL/TA is the ratio of firm's total liabilities to its total assets; CF/TA is the ratio of firm's net operating cash flow to its total assets; MB is the market-to-book ratio of the firm's market capitalization to its total equity; RSIZE is the firm's relative size measured as the log ratio of each firm's market capitalization to that of the ASX All Ordinary Index; MC/TL is the firm's market capitalization divided by its total liabilities. Panel A shows descriptive statistics for all firm-year observations for the entire sample over the period of 1989 – 2006. There are a total of 1,716 non-financial firms and 13,505 firm-year observations in the sample. The description of Panel B is as for Panel A except that it applies to an estimation sample over the period of 1989 – 2002. There are a total of 1,278 non-financial firms and 8,815 firm-year observations in the sample. The description of Panel C is also as for Panel A except that it applies to a holdout sample for the period of 2003 – 2006. There are a total of 1,471 non-financial firms and 4,690 firm-year observations in the sample.

Panel A: Descriptive statistics for the entire sample

Variables	Distress group	N	Mean[1]	Median	Std. Dev.	Minimum	Maximum
NI / TA	Non-failed	13,385	-0.2044408	-0.0144001	0.6490058	-4.6944134	0.3698276
	Failed	120	-1.4259877	-0.1818189	4.9484986	-36.621599	0.3667659
WC / TA	Non-failed	13,385	0.0498244	0.0136517	0.1990892	-0.7378846	0.6911081
	Failed	120	-0.0992059	0.0078747	0.7655856	-4.2500000	0.7887640
TL / TA	Non-failed	13,385	0.3825350	0.3499641	0.3543285	0.0048285	2.3684211
	Failed	120	1.0349375	0.5787598	2.0435304	0.0092766	14.322398
CF / TA	Non-failed	13,385	-0.0660576	0	0.3084523	-1.8497853	0.4167387
	Failed	120	-0.4722762	-0.0597495	1.7888868	-10.618299	0.5881350
MB	Non-failed	13,385	2.4564399	1.5268424	3.7434954	-6.4046426	25.692266
	Failed	120	1.5973045	0.9689144	6.9971732	-24.823141	27.223200
RSIZE	Non-failed	13,385	-4.2615247	-4.4209000	0.9229622	-5.8409512	-1.7255087
	Failed	120	-4.5124554	-4.5851476	0.9716785	-6.2175435	0
MC / TL	Non-failed	13,385	22.596316	3.4666430	53.992915	0.0873250	368.65309
	Failed	120	17.355549	1.2061581	75.842800	0	573.39857

Panel B: Descriptive statistics for estimation sample							
Variables	Distress group	N	Mean[1]	Median	Std. Dev.	Minimum	Maximum
NI / TA	Non-failed	8,735	-0.1890736	-0.0026044	0.6331541	-4.6944134	0.3698276
	Failed	80	-0.7210438	-0.1230941	1.7651057	-10.924480	0.3667659
WC / TA	Non-failed	8,735	0.0616954	0.0255293	0.1993843	-0.7378846	0.6911081
	Failed	80	-0.0573539	0.0393789	0.7473615	-4.2500000	0.7887640
TL / TA	Non-failed	8,735	0.3900234	0.3714161	0.3461527	0.0048285	2.3684211
	Failed	80	0.8629750	0.5870555	1.6768221	0.0092766	14.322398
CF / TA	Non-failed	8,735	-0.0472258	0.0066185	0.2815238	-1.8497853	0.4168856
	Failed	80	-0.3237540	-0.0421652	1.3332033	-10.588315	0.5881350
MB	Non-failed	8,735	2.2352357	1.3698105	3.4939221	-6.4046426	25.692266
	Failed	80	1.6746397	0.8528784	6.7926516	-24.823141	27.223200
RSIZE	Non-failed	8,735	-4.1888888	-4.3521340	0.9305348	-5.8409512	-1.7255087
	Failed	80	-4.4172784	-4.5148183	1.0420785	-6.2175435	0
MC / TL	Non-failed	8,735	20.976386	2.8993440	53.461274	0.0873250	368.65309
	Failed	80	6.2985941	0.8307736	17.876830	0	118.89981

Panel C: Descriptive statistics for holdout sample							
Variables	Distress group	N	Mean[1]	Median	Std. Dev.	Minimum	Maximum
NI / TA	Non-failed	4,650	-0.2333081	-0.0386126	0.6769085	-4.6944134	0.3698276
	Failed	40	-2.8358756	-0.3663879	8.0839024	-36.621599	0.3667659
WC / TA	Non-failed	4,650	0.0275248	-0.0009020	0.1966263	-0.7378846	0.6911081
	Failed	40	-0.1829101	-0.0120981	0.8038793	-4.2500000	0.7085983
TL / TA	Non-failed	4,650	0.3684681	0.3046126	0.3688246	0.0048285	2.3684211
	Failed	40	1.3788624	0.5696045	2.6200512	0.0092766	14.322398
CF / TA	Non-failed	4,650	-0.1014330	-0.0230894	0.3508450	-1.8497853	0.4168856
	Failed	40	-0.7693206	-0.1016838	2.4552539	-10.618299	0.5881350
MB	Non-failed	4,650	2.8719708	1.8390339	4.1407167	-6.4046426	25.692266
	Failed	40	1.4426342	1.2268207	7.4760934	-24.823141	27.223200
RSIZE	Non-failed	4,650	-4.3979710	-4.5520429	0.8928262	-5.8409512	-1.7255087
	Failed	40	-4.7028093	-4.7309524	0.7908544	-6.2175435	-3.1303092
MC / TL	Non-failed	4,650	25.639346	5.0722199	54.854289	0.0873250	368.65309
	Failed	40	39.469459	1.8335542	127.08922	0.0239425	573.39857

Panel D: Descriptive Statistics of NI/TA grouped by Year						
Year	N	Mean	Median	Std. Dev.	Minimum	Maximum
1989	56	0.0541701	0.0528488	0.0922714	-0.2753289	0.3163628
1990	67	0.0199665	0.0517173	0.2000937	-1.2635262	0.3698276
1991	99	-0.0515958	0.0354946	0.4727639	-4.6944134	0.3698276
1992	462	-0.2445626	0.0002112	0.7980315	-4.6944134	0.3045397
1993	520	-0.1191241	0.0132208	0.5720244	-4.6944134	0.3698276
1994	622	-0.0820474	0.0227670	0.4903810	-4.6944134	0.3698276
1995	678	-0.1155786	0.0190306	0.5374183	-4.6944134	0.3698276
1996	735	-0.0774989	0.0132043	0.3641876	-4.6944134	0.3698276
1997	779	-0.1080678	0	0.4014774	-4.9638071	0.3698276
1998	812	-0.1733446	0	0.6198979	-4.6944134	0.3698276
1999	877	-0.1681899	0	0.5646330	-4.6944134	0.3698276
2000	999	-0.1396347	-0.0049617	0.4931552	-4.6944134	0.3698276
2001	1,044	-0.3593912	-0.0401468	0.9277242	-10.9244802	0.3698276
2002	1,065	-0.3696295	-0.0649399	0.9007334	-8.5540541	0.3698276
2003	1,072	-0.3203504	-0.0386937	0.8473606	-7.5795358	0.3698276
2004	1,137	-0.2209747	-0.0294531	0.7211106	-9.2613779	0.3698276
2005	1,224	-0.2237759	-0.0410236	0.6274303	-4.6944134	0.3698276
2006	1,257	-0.2827157	-0.0384873	1.5482209	-36.6215998	0.3698276
Panel E: Descriptive Statistics of NI/TA grouped by Firm Size						
Firm Size (Quartile)	N	Mean	Median	Std. Dev.	Minimum	Maximum
Q1	3376	-0.5247709	-0.1765108	1.1743217	-36.6215998	0.3698276
Q2	3376	-0.2784907	-0.0794690	0.9163825	-36.6215998	0.3698276
Q3	3376	-0.0939643	0.0137022	0.3983990	-4.6944134	0.3698276
Q4	3377	0.0341840	0.0499120	0.1886210	-4.6944134	0.3698276

[1] Wilcoxon-Mann-Whitney test is carried out for each variable to test the significance of differences of firm characteristics between failed and non-failed groups. The test shows the differences are statistically significant at the 1% level for all variables except for the WC/TA for the entire sample and estimation sample, and at the 5% level for all variables, with the exception of WC/TA, for holdout sample.

Table IV
Correlation matrix

This table presents the Pearson Product-Moment correlations. Pearson correlation statistics are computed from observations with non-missing values for each pair of predictor variables. All correlations are significant at the 1% level (two-sided test). NI/TA is the firm's net income divided by its total assets; WC/TA is the firm's working capital divided by its total assets; TL/TA is the ratio of firm's total liabilities to its total assets; CF/TA is the ratio of firm's net operating cash flow to its total assets; MB is the market-to-book ratio of the firm's market capitalization to its total equity; RSIZE is the firm's relative size measured as the log ratio of each firm's market capitalization to that of the ASX All Ordinary Index; MC/TL is the firm's market capitalization divided by its total liabilities. Correlation matrices of the seven covariates in the model are constructed for the entire sample (Panel A), the estimation sample (Panel B) and the holdout sample (Panel C), respectively. Panel A shows the correlation matrices constructed based on 13,505 all firm-year observations from 1989 – 2006 including 120 failed firms. Panel B is constructed using the estimation sample, where there are 8,815 firm-year observations from 1989 – 2002 including 80 failed firms. Panel C is constructed on a holdout sample, where there are 4,690 firm-year observations from 2003 – 2006 including 40 failed firms.

Panel A: Correlation matrix for the entire sample

Variables	NI / TA	WC / TA	TL / TA	CF / TA	MB	RSIZE	MC / TL
NI / TA		0.355	-0.329	0.652	-0.063	0.258	-0.053
WC / TA			-0.301	0.300	-0.057	0.108	0.015
TL / TA				-0.169	-0.080	0.069	-0.311
CF / TA					-0.123	0.333	-0.136
MB						0.120	0.229
RSIZE							-0.112
MC / TL							

Panel B: Correlation matrix for estimation sample

Variables	NI / TA	WC / TA	TL / TA	CF / TA	MB	RSIZE	MC / TL
NI / TA		0.331	-0.253	0.666	-0.052	0.290	-0.049
WC / TA			-0.254	0.240	-0.046	0.082	0.040
TL / TA				-0.079	-0.075	0.073	-0.321
CF / TA					-0.110	0.326	-0.142
MB						0.138	0.238
RSIZE							-0.103
MC / TL							

Panel C: Correlation matrix for holdout sample

Variables	NI / TA	WC / TA	TL / TA	CF / TA	MB	RSIZE	MC / TL
NI / TA		0.401	-0.416	0.642	-0.070	0.230	-0.058
WC / TA			-0.386	0.382	-0.058	0.136	-0.020
TL / TA				-0.281	-0.083	0.059	-0.295
CF / TA					-0.126	0.341	-0.123
MB						0.118	0.208
RSIZE							-0.117
MC / TL							

Table V
Hazard model estimates

Panel A shows the total number of firms, the number of failed firms and the number of censored (non-failed) firms and percentages of censored to the total number of firms in our estimation sample over the period of 1989 – 2002. Panel B reports the parameter estimates of Cox hazards model with time-varying covariates, $h_i(t \mid z(t)) = h_0(t) \cdot \exp\left\{ \sum_{j=1}^{p} \beta_j z_j^i(t) \right\}$. NI/TA is the firm's net income divided by its total assets; WC/TA is the firm's working capital divided by its total assets; TL/TA is the ratio of firm's total liabilities to its total assets; CF/TA is the ratio of firm's net operating cash flow to its total assets; MB is the market-to-book ratio of the firm's market capitalization to its total equity; RSIZE is the firm's relative size measured as the log ratio of each firm's market capitalization to that of the ASX All Ordinary Index; MC/TL is the firm's market capitalization divided by its total liabilities. A positive coefficient on a particular variable implies that the hazard rate is increasing in that variable.

Panel A: Number of failed and censored firms in the estimation sample

Total	Failed	Censored	Percent Censored
1,278	80	1,198	93.74

Panel B: Parameter estimates

Variables	Expected sign	Coefficient	Std. Error	Chi-Square	*p*-Value
NI / TA	-	-0.06714	0.11583	0.3360	0.5621
WC / TA	-	-0.31114	0.27851	1.2480	0.2639
TL / TA	+	0.32142	0.07622	17.7809	<.0001
CF / TA	-	-0.60997	0.16368	13.8875	0.0002
MB	+	0.02143	0.02354	0.8291	0.3625
RSIZE	-	-0.15080	0.12955	1.3549	0.2444
MC / TL	-	-0.02896	0.01132	6.5483	0.0105

Panel C: Log Likelihood Statistics

Criterion	Without Covariates	With Covariates
-2 LOG L	1058.940	1000.033

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	58.9066	7	< .0001

Table VI
The time-dependent risk scores and survival probabilities of twenty firms selected from estimation sample

This table presents dynamic changes of risk scores (Score) and survival probabilities (P(S)) by time horizon using a time-dependent Cox regression model, $h_i(t \mid z(t)) = h_0(t)\cdot \exp\left\{\sum_{j=1}^{p}\beta_j z_j^i(t)\right\}$, for twenty randomly selected firms. The time-dependent risk score can be calculated for each firm as $\hat{\beta} * z_i(t)$, where $\hat{\beta}$ is a vector of estimated coefficients shown in Table V and $z_i(t)$ is a vector of values of covariates for firm *i* at time *t*. The survival probabilities are calculated using $\hat{h}_i(t) = \hat{h}_0(t) \times \exp\left(\hat{\beta}\cdot z_i(t)\right)$ and $\hat{S}_i(t) = \exp\left[-\int \hat{h}_i(u)du\right]$ in Section 3.3 and the estimated risk scores. Panel A shows the resulting risk scores and survival probabilities for ten non-failed firms, and Panel B shows those for ten failed firms. Each firm has its own life time and the risk score and the survival probabilities are generated for different time horizons.

Panel A: 10 Non-failed firms from Estimation Sample

Firm (*i*)	Firm 1		Firm 2		Firm 3		Firm 4		Firm 5		Firm 6		Firm 7		Firm 8		Firm 9		Firm 10	
Lifetime (yrs)	4		5		6		7		8		9		11		12		13		14	
Status	Non-failed		Non-failed		Non-failed		Non-failed		Non-failed		Non-failed		Non-failed		Non-failed		Non-failed		Non-failed	
Time horizon	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)
0	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000
1	0.8028	0.9995	0.4400	0.9995	0.6588	0.9995	0.6066	0.9995	0.0218	0.9995	0.6523	0.9995	1.3563	0.9995	0.7058	0.9995	0.4239	0.9995	0.4048	0.9995
2	0.7545	0.9984	0.4351	0.9987	0.7027	0.9985	0.4902	0.9986	0.6080	0.9990	0.8000	0.9985	0.9727	0.9976	0.6949	0.9985	0.4559	0.9987	0.4308	0.9988
3	1.1560	0.9971	0.0414	0.9978	0.8610	0.9973	0.6801	0.9976	0.4035	0.9978	0.8302	0.9972	0.2843	0.9959	0.6774	0.9972	0.4299	0.9978	0.2543	0.9978
4	1.4228	0.9950	0.6898	0.9971	0.9348	0.9958	0.6190	0.9963	0.4383	0.9969	0.9850	0.9957	0.4504	0.9951	0.5802	0.9960	0.2854	0.9968	0.2694	0.9970
5	1.4228	0.9923	1.2470	0.9958	0.9608	0.9941	0.6850	0.9951	0.5995	0.9959	1.0386	0.9939	0.217	0.9941	0.6907	0.9948	-0.043	0.9959	0.292	0.9961
6			1.2470	0.9933	1.0440	0.9922	0.6362	0.9936	0.3294	0.9945	1.5352	0.9919	0.2149	0.9931	0.5620	0.9934	0.2558	0.9952	0.2837	0.9951
7					1.0440	0.9900	0.4957	0.9922	0.5185	0.9935	0.6586	0.9883	0.0675	0.9922	0.4963	0.9920	0.4934	0.9942	0.347	0.9941
8							0.4957	0.9908	0.5185	0.9921	1.3838	0.9867	-0.665	0.9913	0.5995	0.9906	0.3288	0.9928	0.367	0.9929
9									0.5185	0.9902	1.3838	0.9824	0.5837	0.9907	0.5811	0.9887	0.5583	0.9913	0.3339	0.9914
10											1.3838	0.9776	0.5837	0.9886	0.6361	0.9865	0.9357	0.9892	0.4064	0.9897
11													0.5837	0.9795	0.6516	0.9769	0.9361	0.9763	0.4798	0.9820
12													0.5837	0.9795	0.7558	0.9160	0.7962	0.8962	0.5261	0.9302
13															0.7558	0.9160	0.7715	0.8319	0.6016	0.8788
14																	0.7715	0.7737	0.5217	0.8266
15																			0.5217	0.8266

Panel B: 10 Failed firms from Estimation Sample

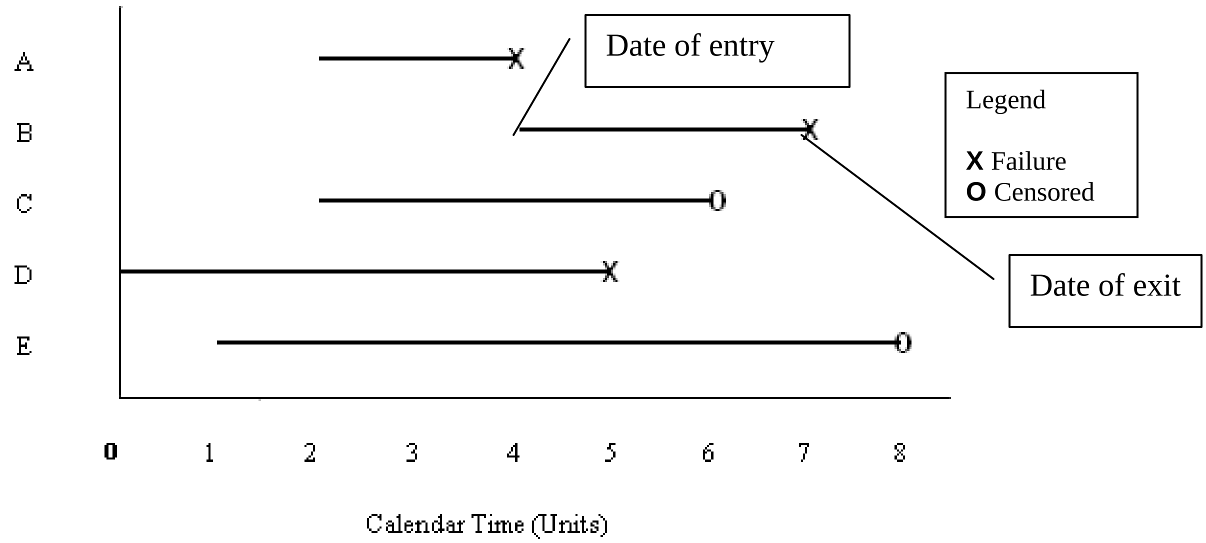
Firm (i)	Firm 11		Firm 12		Firm 13		Firm 14		Firm 15		Firm 16		Firm 17		Firm 18		Firm 19		Firm 20	
Lifetime (yrs)	4		5		5		6		7		7		9		10		11		14	
Status	Failed		Failed		Failed		Failed		Failed		Failed		Failed		Failed		Failed		Failed	
Time horizon	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)
0	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000
1	1.4936	0.9995	1.3745	0.9995	-3.898	0.9995	-1.037	0.9995	0.6032	0.9995	0.4369	0.9995	0.6551	0.9995	1.2259	0.9995	-2.463	0.9995	0.3137	0.9995
2	1.6396	0.9973	0.0944	0.9975	0.7498	0.9995	0.7977	0.9993	0.5968	0.9986	0.7611	0.9987	0.3236	0.9985	-3.445	0.9978	-4.503	0.9995	0.3080	0.9988
3	1.4639	0.9941	0.7405	0.9968	0.9677	0.9982	2.5463	0.9979	0.8151	0.9975	0.7462	0.9974	0.2843	0.9977	-3.729	0.9978	0.8189	0.9994	0.2666	0.9980
4	5.8930	0.9913	0.9996	0.9955	0.7836	0.9965	1.3804	0.9898	0.9945	0.9960	0.7792	0.9960	0.2551	0.9968	-1.513	0.9978	0.6777	0.9980	0.4767	0.9971
5	5.8930	0.7824	1.0201	0.9937	5.0650	0.9951	2.2117	0.9872	1.5925	0.9942	0.9689	0.9946	-0.493	0.9960	0.7626	0.9976	0.7775	0.9967	0.2738	0.9961
6			1.0201	0.9917	5.0650	0.8861	0.8663	0.9806	4.0695	0.9907	0.9926	0.9927	0.2650	0.9955	0.9821	0.9961	0.7620	0.9951	0.3614	0.9951
7							0.8663	0.9788	4.0695	0.9461	1.0542	0.9906	2.0366	0.9945	1.0166	0.9940	0.8826	0.9934	0.4065	0.9940
8									4.0695	0.9013	1.0542	0.9883	2.0732	0.9882	0.7063	0.9917	1.2585	0.9915	-0.873	0.9928
9													1.1564	0.9796	2.3641	0.9895	2.0551	0.9876	-1.250	0.9923
10													1.1564	0.9754	4.9677	0.9767	2.0551	0.9782	-0.405	0.9920
11															4.9677	0.4648	2.0551	0.9396	-0.096	0.9885
12																	2.0551	0.9396	-0.078	0.9589
13																			0.5949	0.9296
14																			0.8267	0.8747
15																			0.8267	0.8747

Table VII
Predictive Accuracy

This table shows the area under the ROC (AUROC) curve of the in-sample and out-of-sample survival functions. The AUROC measures the predictive accuracy of the model and the higher the AUROC, the better the model. Predictions made at random have an AUROC of 0.5 and models that do not beat this benchmark have no predictive power. Panel A examines predictive accuracy over the period for which we have estimation sample from 1989 to 2003. The estimation horizon is presented with event time, from 1 to 14 years. Panel B describes the area under the ROC curve for holdout sample. Holdout sample is reserved for the purpose of out-sample prediction, and whose predictive accuracy is tested against the estimated time-dependent Cox hazards model.

Panel A: Predictive accuracy over estimation sample – Area under the ROC curve for in-sample prediction	
Estimation Horizon	AUROC
1	0.4612441
2	0.4887909
3	0.6408263
4	0.6411966
5	0.6646468
6	0.6500862
7	0.6365567
8	0.6428241
9	0.6608045
10	0.6519414
11	0.7000067
12	0.7426942
13	0.7929476
14	0.8106618
Panel B: Predictive accuracy over holdout sample – Area under the ROC curve for out-of-sample prediction	
Forecast Horizon	AUROC
1	0.6075342
2	0.6706679
3	0.6960380
4	0.6661926

Figure 1
Calendar time vs. Event time
Panel A: Arrangement of Firms in the Risk set according to calendar time



Panel B: Arrangement of Firms in the Risk set according to Event Time

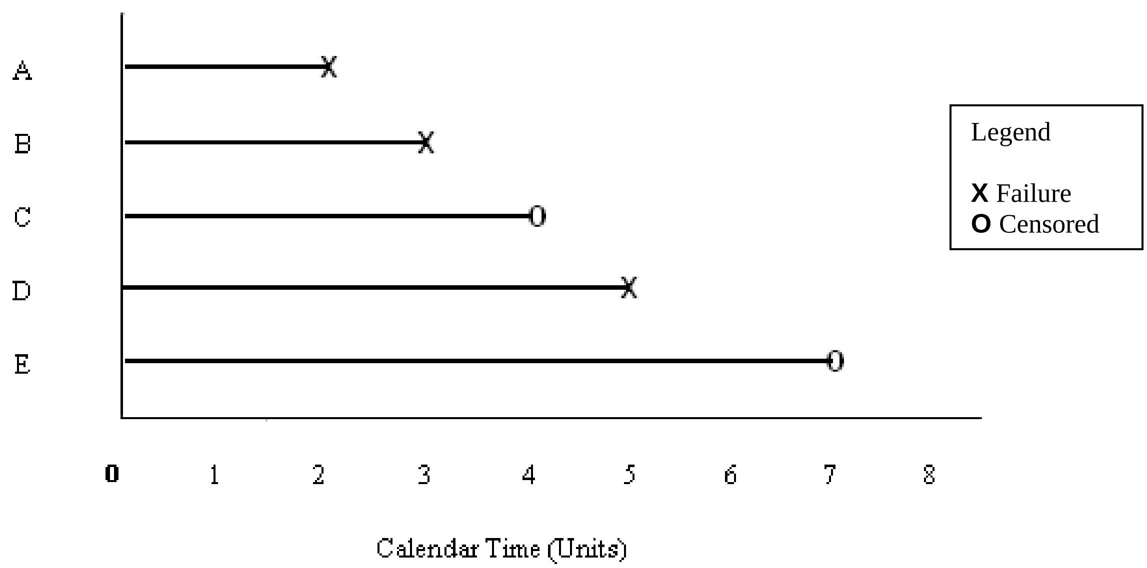


Figure 2
Calculation of the Likelihood for the Failure of Firm A in a Time-dependent Model