Evaluating Firms in Financial Distress: An Event History Analysis

Dr. Nancy Thorley Hill, School of Accountancy, DePaul University
Dr. Susan E. Perry, McIntire School of Commerce, University of Virginia
Dr. Steven Andes, Public Services Department, DePaul University

Abstract

This study uses event history methodology and dynamic models to examine bankruptcy and financial distress. Dynamic models incorporate the conditional probability of a firm's financial status changing from financially distressed to stable or bankrupt and enable us to simultaneously examine stable, financially distressed and bankrupt firms. We also add to the literature by incorporating two economic indicator variables and extend prior research with an analysis by industry segment.

Introduction

The purpose of this research is to examine accounting information's role in identifying firm bankruptcy and financial distress. We extend existing bankruptcy research by using a dynamic event history methodology to distinguish between financially distressed firms that survive and those that become bankrupt. Because most distressed firms do not become bankrupt, a critical examination of those that do may provide additional insights into the failure process (Jones 1987; Gilbert et al. 1990; Flagg et al. 1991). A methodology that allows for dynamic analysis is appropriate because movement to and from financial distress or to bankruptcy is a dynamic process that begins with some initial conditions and incorporates changes in these conditions over time (i.e., fluctuations in financial ratios, other financial measures, and economic indicators).

Because of the potential benefit to investors, lenders, management, employees or their unions, and auditors, ongoing research in this area continues to refine and test bankruptcy and financial distress models. These models are typically based on a set of financial variables and are examined using multiple discriminant analysis and logit or probit analysis. We use event history methodology and dynamic models which allow for time-varying explanatory variables and control for censored observations - two key data characteristics that create significant difficulties for standard statistical models. Bankruptcy is a change in firm financial status and therefore it is appropriate to measure the explanatory financial variables during the years preceding distress and bankruptcy. Dynamic models exploit the interaction of the change in explanatory variables and the firm's financial status (i.e., stable, financially distressed or bankrupt) in each year of the observation period and allow us to calculate a "transition rate" or conditional probability of a change in a firm's financial status. Similar to logit and probit analysis, estimated parameters from dynamic models identify significant characteristics related to changes in a firm's financial status.

In addition to our dynamic analysis, other differences between our study and previous bankruptcy research include the following. First, simultaneous examination of stable, financially distressed, and bankrupt firms allows us to compare the resulting parameters for each financial state.

This enables us to test directly the finding from previous studies that the variables that describe bankruptcy differ from those that describe distress. Second, we group our sample into two broad industry classifications to examine possible differences in the failure process and significant variables across classes of firms. Third, we include in our dynamic models 1) financial ratios suggested from prior research, 2) a measure indicating whether each firm received a qualified or unqualified audit opinion, and 3) the effects of two leading economic indicator variables - the unemployment rate and prime rate. Finally, while prior studies often involve a proportion of bankrupt firms much larger than found in the population, our sample includes all bankrupt, financially distressed, and stable firms in the population of NYSE and AMEX firms from 1977-1987. We limit this population with only one criterion which requires that each firm experience financial distress at least once over the 11 year period.

The following section discusses strengths and weaknesses of prior research and methodologies. The third section provides the theory of event history analysis and its benefits. The sample and variables are presented in the fourth section and the results, conclusion, and suggestions for future research complete the paper.

Prior Research

Starting with the pioneer research of Beaver (1966), Altman (1968), and Altman et al. (1977), studies based on various methodologies show that financial variables are correlated with bankruptcy. Early work utilizing discriminant analysis (e.g., Beaver 1966; Altman 1968; Dambolena and Khoury 1980), however, has statistical limitations (e.g. Zavgren 1983; Mensah 1984; Jones 1987). To address problems inherent in discriminant analysis, researchers utilize logit and probit analysis (e.g., Ohlson 1980; Zavgren 1985) but the methodology is not always applied correctly. For example, many studies oversample the bankrupt group of firms by selecting a sample of bankrupt and stable firms on a one to one basis even though the percentage of business failures in the population is less than 1.2%.[1] Zmijewski (1984) points out that biased coefficient estimates and understated classification and prediction error rates result from oversampling bankrupt firms. However, there are adjustment procedures available to the researcher that 1) use weights based on prior probabilities in the estimation process and 2) determine the optimal cut-off point to minimize prediction error rates and classification costs.[2] The small number of bankrupt firms also leads researchers to pool data over several years, creating a second potential problem. For example, if independent variables are not stable over time or if other economic factors related to bankruptcy and financial distress are not controlled for, the results may be misleading (Zavgren, 1983; Mensah, 1984).

A few studies take a longitudinal approach in analyzing firms' progression toward bankruptcy by estimating logit or probit models at one to five years prior to bankruptcy (e.g., Zavgren 1985; Hopwood et al. 1989). The parameters and statistical significance are then compared over the years to reveal variables that indicate bankruptcy. This cross-sectional design, however, only provides a snap-shot of ratio measures in each year and does not truly capture the dynamic process of distress and recovery or bankruptcy.

Much of prior research focuses on bankrupt versus stable firms, but as Jones suggests "accuracy in predicting bankruptcy among marginal companies, rather than quite healthy and quite distressed companies, may be the real test of a model's usefulness" (Jones 1987, p. 147). Recent research specifically identifies and documents the importance of examining financially distressed firms in bankruptcy prediction models. A bankruptcy prediction model that distinguishes between financially distressed firms that survive and financially distressed firms that ultimately go bankrupt offers incremental information to that learned from modeling stable firms and bankrupt firms. In fact, Gilbert et al. (1990) find different statistically significant explanatory financial variables for financially distressed versus bankrupt groups and stable versus bankrupt groups. Hopwood et al. (1993) also examine stressed and non-stressed firms where each group includes firms that declared bankruptcy. They also report that statistically significant variables differ between these two groups.

Flagg et al. (1991) examine only financially distressed firms and identify two failure events and four financial ratios as significant in discriminating between bankrupt and non-bankrupt firms.

We also note that in addition to financial ratios, other measures related to firm failure are considered by researchers. First, studies examining auditors' ability to predict bankruptcy suggest that a qualified opinion may serve as a warning signal for bankruptcy. For example, Hopwood et al. (1989, 1993), and Flagg et al. (1991) find that a qualified opinion is significant in distinguishing failed firms. Second, to control for changes in the business environment, researchers may need to include macroeconomic variables. "Rising interest rates, a recessionary environment, the availability of credit" may affect a firm's change in financial status (Zavgren 1983, p. 32). These variables have typically been omitted in prior research but are investigated by Rose et al. (1982). They examine 28 business cycle indicators and find that economic conditions affect the failure process.

Finally, prior studies attempt to control for industry differences by limiting the industries selected for the sample, by matching failed and stable firms by industry classification, or by standardizing firm specific financial ratios by industry ratios (e.g., Barnes 1987; Platt and Platt 1990; 1991). These methods, however, do not enable us to test whether some variables have a statistically significant impact on bankruptcy or financial distress for some industries and not for others.

The next section discusses event history methodology and how it addresses the limitations in cross-sectional based research noted above.

Event History Methodology

The use of dynamic models is one technique among a set of techniques known as event history analysis in the economic and sociological literature.[3] Dynamic models have been used when the question of interest involves choice or status over time, for example, duration of unemployment and time to adoption of new technologies.

While recent research in bankruptcy and financial distress uses a cross-sectional approach, event history analysis may provide new and valuable insights in analyses of bankruptcy for the following reasons. Event history analysis considers independent variables over time and their impact on the dependent variable of interest. Rather than a snap-shot in time (a cross-sectional analysis), event history analysis incorporates and considers the changes in independent variables over time (using longitudinal data). Event history does not merely look at the level of a variable at a given time. This is an important distinction between cross-sectional and event history analysis. Further, the snap-shot or cross-sectional focus assumes, in the model, that a sample firm (which is stable, financially distressed, or bankrupt) will remain in that state. The cross-sectional analysis misses information that may indicate, for example, that a firm is *not* going to remain in its current state, but is "transitioning to" or will become bankrupt in next year. In other words, the independent variables, if considered over time, may indicate that a firm is moving toward financial distress or moving from financial distress toward bankruptcy. A snap-shot analysis is unable to capture this information and assumes that a firm with these independent variable measurements will remain in this state forever.

The dynamic model employed in our study addresses and corrects for the problems inherent in cross-sectional studies in four ways.[4] First, dynamic models include a measure of the dependent variable which indicates the "state" of the firm (stable, financially distressed or bankrupt) as well as the length of time in a particular state.[5] Cross-sectional analysis typically measures the financial "state" only once. Second, the dynamic model explicitly accounts for time-varying independent variables which may change over the observation period. Prior studies which draw inferences from a series of models (typically estimated at one to five years prior to bankruptcy) measure a variable "level" associated with a particular financial state and therefore changes in independent variables are not accounted for. Third, the likelihood that a sample firm becomes financially distressed or enters into bankruptcy in the *future* (outside the observation period) is not considered in cross-sectional analysis. Event history methodology, however, includes the likelihood that a firm will become financially distressed or enter into bankruptcy in the future. This likelihood or probability is conditional upon whether the firm is financially distressed or bankrupt at a particular point in time. Assessing the "conditional probability" is the central concept of the dynamic models. For these models, firms which are not financially distressed or bankrupt by the end of the observation period are classified as "censored" observations - firms that have not moved to the financially distressed or bankrupt state but are still "at risk". In contrast, cross-sectional analysis, based on unconditional probabilities, includes sample firms not financially distressed or bankrupt at the end of the observation period as firms which would never become financially distressed or bankrupt. Finally, cross-sectional analysis assumes the process being modeled is in equilibrium and ignores trends or changes in the process. Event history analysis does not assume equilibrium, but rather models the change in the process through "transition rates." The event history models are presented and discussed in the Appendix.

Method

Sample selection and data collection

The sample includes all NYSE and AMEX firms which experienced financial distress at least once during 1977-1987. Financially distressed firms are defined as those firms having cumulative negative earnings over any three year period from 1977-1987.[6] We identified firms filing for bankruptcy during the 1979-1987 time period from the *Wall Street Journal Index* and the *Capital Changes Reporter*. Financial data for all financially distressed or bankrupt firms were obtained from the COMPUSTAT Industrial Annual tape or the COMPUSTAT Annual Research tape (which includes firms removed from the annual COMPUSTAT file due to bankruptcy, mergers or acquisitions). The firms were grouped into two broad industries: manufacturing firms (mining, oil and gas, and chemical firms; manufacturing of food, apparel, paper, printing, and leather firms; metal, industrial machines and equipment firms) and wholesale, retail and service firms. Firms from other industries were deleted (e.g., financial institutions, transportation and utility firms). We also excluded firms that went bankrupt without experiencing financial distress because sudden bankruptcy may *not* be a result of financial distress. Hopwood et al. (1993) suggest that bankruptcy not preceded by financial distress is more likely to be driven by management fraud, and Jones (1987) points out that it might reflect a strategic decision to void a union contract or avoid a liability judgment. We concur that, in general, most firms filing for bankruptcy would likely experience financial distress for some period prior to bankruptcy and that financially *stable* firms which file for bankruptcy may have firm specific reasons for the filing. We therefore constrain our sample to firms experiencing at least one year of financial distress prior to bankruptcy. We identified 75 bankrupt firms over the 1979-1987 period for the two industry groups. All firms were then coded for each year of data as financially stable, financially distressed or bankrupt. The sample includes 381 firms over the 11 year period where some firms declare bankruptcy and drop out of the sample and other firms are added. On average, the sample has 257 firms in any given year.

Variables

As noted in prior studies, the lack of a theoretical model of bankruptcy leads researchers to choose and examine possible variables from a set of measures thought to be significant in explaining financial stability, distress or bankruptcy. The choice of variables may rely on tests of statistical significance or step-wise regression. While an "appropriate" set of ratios has not been theoretically derived, prior research finds measures of liquidity, profitability, and leverage significant in explaining bankruptcy (Zmijewski 1984; Hopwood et al. 1989; Gilbert et al. 1990; Flagg et al. 1991; Platt, 1995). Measures such as size, operating ratios and economic indicators are also included in bankruptcy models (Rose et al. 1982; Platt and Platt 1990; Platt 1995) and have been shown to be related to bankruptcy.

Following prior research, we calculate and test a series of financial ratios which may explain a firm's financial state.[7] For comparability, we include measures of liquidity, profitability, leverage, and firm size. Since many ratios can provide measures of liquidity, profitability, leverage, and firm size, we select measures that are highly correlated with the dependent variables yet show low correlation with other independent variables. Finally, the selected ratios are adjusted for industry averages (Platt and Platt, 1991).[8] We also include an indicator variable identifying the specific years when firms receive qualified opinions. We use data obtained from COMPUSTAT to calculate the following independent variables for the model:

Liquidity - Cash to Total Assets
Profitability - Income before Extraordinary Items to Total Assets
Leverage - Total Liabilities to Total Assets
Size - Natural Log of Sales
Qualified Opinion (coded as 0 in years of unqualified opinions, otherwise 1)[9]

In addition to sample firms' specific data for each year, we include two leading economic indicators: the prime rate and unemployment rate.[10] High interest rates and fluctuating unemployment rates affect a firm's ability to borrow, it's future cash flows, and the overall health of the firm. Both the prime rate and unemployment rate are identified by Rose et al. (1982) as leading business failure and are included as a one year lag in the model.

An event history format is employed where each firm is assigned a "spell" for every year. A "spell" includes measures of the dependent variable (the firm's financial state) and the associated independent variables. The progression of spells represents the history of the firm over time. Maximum likelihood is used to estimate the parameters using Tuma's (1982) RATE program. It combines censored and uncensored observations to produce estimates that are asymptotically unbiased, normally distributed and efficient (Allison 1984; Tuma et al. 1984).

Results

Table 1 provides descriptive statistics for the financial and economic variables for the overall sample and for the firms grouped by financial status and industry. We compare means grouped by financial status (stable versus financially distressed, stable versus bankrupt, and financially distressed versus bankrupt firms) and find means to be significantly different at $p < 0.05$. Bankrupt firms have lower liquidity ratios, are less profitable, more highly leveraged, and smaller than financially distressed firms and stable firms. With the exception of liquidity, mean ratios for financially distressed firms generally fall between stable and bankrupt firms indicating that it may be more difficult to distinguish between financially distressed and either stable or bankrupt firms. We also find that the lag of the unemployment and prime rates for firms in a bankruptcy year tend to be higher than during the stable or financially distressed years as suggested in prior research.

Table 1 also shows mean comparisons by industry. Even though the ratios have been adjusted for industry average, we find statistically significant differences ($p < 0.05$) in the means for the independent variables between the two industry groups for the Profitability, Leverage and Size variables. It appears that industry effects are important for models which attempt to identify the impact of significant variables on bankruptcy and financial distress. For example, the mean profitability ratio is negative for the manufacturing firms and positive for the retail firms.

Table 2 reports the Pearson Correlation Coefficients for the dependent and independent variables and suggests the correlations between independent variables are modest. Analysis of correlations by industry group (not reported) are similar.

Table 3 provides results of the dynamic model for the full sample as well as for subsamples based on two industry groups (manufacturing firms and wholesale, retail, service firms). For the entire sample (Panel A), five variables, Liquidity, Leverage, Size, Qualified Opinion and Prime Rate, are statistically significant at $p < 0.05$ for financially distressed firms. For bankrupt firms, we find that Profitability, Leverage, Size, Qualified Opinion, the Unemployment Rate and Prime Rate are significant ($p < 0.05$). While several variables are significant for both financially distressed and bankrupt firms, these results suggest that other ex-

Table 1
Descriptive Statistics

	All firms 1977-1987		By Financial Status				By Industry	
			Stable	Fin'cially dis-tressed	Bank-rupt		Manufac-turing Firms	Wholesale, Retail, & Service Firms
Explanatory Variables [a]	Mean (Std.Dev) n=2829		Mean (Std.Dev) n=1443	Mean (Std.Dev) n=1311	Mean (Std.Dev) n=75		Mean (Std.Dev) n=2073	Mean (Std.Dev) n=756
Liquidity	1.209 (0.141)		1.135 (1.296)	1.311 (1.534)	0.867 (1.469)		1.213 (1.442)	1.198 (1.318)
Profitability	-0.041 (6.233)		0.743 (4.834)	-0.620 (6.929)	-4.983 (11.686)		-0.223 (5.361)	0.460 (8.141)
Leverage	1.170 (0.528)		1.119 (0.461)	1.207 (0.577)	1.516 (0.665)		1.189 (0.539)	1.120 (0.494)
Size	0.808 (0.304)		0.848 (0.306)	0.770 (0.297)	0.698 (0.286)		0.775 (0.298)	0.898 (0.303)
Lag - Unemployment Rate	8.508 (3.377)		8.303 (3.236)	8.651 (3.447)	9.960 (4.254)		8.495 (3.361)	8.543 (3.423)
Lag - Prime Rate	11.298 (3.536)		10.464 (3.649)	12.111 (3.185)	13.162 (3.154)		11.300 (3.540)	11.295 (3.527)
Number of Observations with Qualified Opinions	842		328	460	54		612	230

[a] Liquidity - Cash to Total Assets
Profitability - Income before Extraordinary Items to Total Assets
Leverage - Total Liabilities to Total Assets
Size - Natural Log of Sales
Lag - Unemployment Rate - 1 year lag
Lag - Prime Rate - 1 year lag
Qualified Opinion (coded as 0 in years of unqualified opinions, otherwise 1)

planatory variables play a differential role in financial distress and bankruptcy. For example, while Liquidity, a measure of cash, is significant in identifying financially distressed firms, it is not significant for bankrupt firms.

Event history analysis allows us to interpret the sign of parameters as follows. For a unit *increase* in Profitability, the probability of a firm going bankrupt *decreases* as indicated by the negative coefficient (-0.037) for Profitability. In contrast, as Leverage *increases*, the probability a firm will go bankrupt *increases* as indicated by the positive coefficient on Leverage (0.509). To interpret the estimated parameters, we relate the esti mate to the log of the transition rate. For the bankrupt firms, as Leverage increases, the log of the transition increases by 0.509, controlling for other variables. By exponentiating the coefficient (taking the antilog), a more intuitive interpretation is obtained. For unit increases in Leverage, the risk of bankruptcy (the transition rate) changes by a multiple of 1.7 (exp(0.509)=1.7). So, for example, if the hazard rate for bankruptcy is 5%, then for a unit increase in leverage, the hazard rate increases to 7% (1.4 times the hazard rate of 5%). In other words, the probability of bankruptcy for a firm with a leverage ratio (total liabilities to total assets) of 3:1 is 1.4 times greater than for a firm with a leverage ratio of 2:1. This is consistent with

Table 2
Correlations
All firms (1977-1987)

	Liquidity	Profitability	Leverage	Size	Qualified Opinion	Lag-Unemployment Rate	Lag - Prime Rate	Financial State (Dep.Var)
Liquidity [a]	1.000 [b] (0.0) 2829	0.026 (0.168) 2829	-0.258 (0.001) 2829	-0.165 (0.001) 2829	-0.009 (0.633) 2823	0.019 (0.312) 2829	0.047 (0.012) 2829	0.037 (0.048) 2829
Profitability		1.000 (0.0) 2829	-0.101 (0.001) 2829	0.103 (0.001) 2829	-0.136 (0.001) 2823	-0.070 (0.001) 2829	-0.054 (0.004) 2829	-0.155 (0.001) 2829
Leverage			1.000 (0.0) 2829	-0.009 (0.635) 2829	0.081 (0.001) 2823	0.003 (0.867) 2829	-0.003 (0.880) 2829	0.121 (0.001) 2829
Size				1.000 (0.0) 2829	-0.085 (0.001) 2823	0.018 (0.344) 2829	-0.014 (0.451) 2829	-0.141 (0.001) 2829
Qualified Opinion					1.000 (0.0) 2823	0.025 (0.183) 2823	-0.0426 (0.015) 2823	0.189 (0.001) 2823
Lag - Unemployment Rate						1.000 (0.0) 2829	0.142 (0.001) 2829	0.077 (0.001) 2829
Lag - Prime Rate							1.000 (0.0) 2829	0.244 (0.001) 2829

[a] Liquidity - Cash to Total Assets
Profitability - Income before Extraordinary Items to Total Assets
Leverage - Total Liabilities to Total Assets
Size - Natural Log of Sales
Qualified Opinion (coded as 0 in years of unqualified opinions, otherwise 1)
Lag - Unemployment Rate - 1 year lag
Lag - Prime Rate - 1 year lag
Financial State - 0=stable, 1=financially distressed, 2=bankrupt

[b] Correlation coefficient
(Standard deviation)
Number of observations

theory which suggests that as leverage increases, the likelihood of bankruptcy increases. Similarly, for every unit increase in Profitability, the likelihood of bankruptcy changes by a multiple of 0.96 (exp(0.509)=0.96). Since this multiple is less than one, the likelihood of bankruptcy decreases, as the negative parameter sign suggests.

The event history analysis also allows us to compare magnitudes of coefficients across the dependent variable state (stable, financially distressed, and bankrupt).[11] For example, we can conclude that for a unit increase in the Prime Rate, the likelihood of bankruptcy changes by a multiple of 1.16 (exp(0.148) = 1.16) while for financially distressed firms, the probability of becoming financially distressed changes by a multiple of 1.06 (exp(-0.061) = 1.06). This implies that a change in Profitability has a greater impact on the transition rate for bankruptcy than the transition rate for financial distress. As the prime rate increases, the rate of bankruptcy increases faster than the rate of

Table 3
Parameter Estimates for Financial Distress and Bankruptcy Models

	Panel A All Firms		Panel B Manufacturing Firms		Panel C Wholesale, Retail, and Service Firms	
	Financially Distressed State	Bankruptcy State	Financially Distressed State	Bankruptcy State	Financially Distressed State	Bankruptcy State
Explanatory Variables [a]	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Liquidity	0.042* (0.019)	-0.184 (0.116)	0.041* (0.022)	-0.178 (0.142)	0.045 (0.037)	-0.194 (0.214)
Profitability	-0.008* (0.004)	-0.037*** (0.011)	-0.008 (0.005)	-0.040*** (0.014)	-0.006 (0.007)	-0.033 (0.022)
Leverage	0.125** (0.051)	0.509*** (0.170)	0.120** (0.060)	0.695*** (0.201)	0.158 (0.100)	0.188 (0.313)
Size	-0.318*** (0.090)	-0.844** (0.380)	-0.346 (0.113)	-1.109** (0.511)	-0.365** (0.171)	-0.527 (0.604)
Qualified Opinion	0.219*** (0.059)	1.533*** (0.269)	0.194*** (0.070)	1.087*** (0.317)	0.237** (0.111)	2.609*** (0.628)
Lag -Unemploy. Rate	0.004 (0.008)	0.073** (0.028)	0.009 (0.008)	0.092*** (0.035)	-0.011 (0.016)	0.033 (0.051)
Lag- Prime Rate	0.061** (0.007)	0.148*** (0.032)	0.056*** (0.009)	0.170*** (0.041)	0.072*** (0.014)	0.105* (0.055)
Intercept	-7.43*** (0.185)	-12.70*** (0.696)	-7.416*** (0.182)	-13.15*** (0.891)	-7.382*** (0.306)	-12.13*** (1.226)
Chi-squared (D.F.)	115.77*** (7 d.f)	121.61*** (7 d.f.)	76.20*** (7 d.f.)	86.16*** (7 d.f.)	44.31*** (7 d.f.)	45.53*** (7 d.f.)
# Observations (Total = 2829)	1311 Financially Distressed	75 Bankrupt	944 Financially Distressed	50 Bankrupt	367 Financially Distressed	25 Bankrupt

*** Significant at $p < 0.01$
** Significant at $p < 0.05$
* Significant at $p < 0.10$

[a] Liquidity - Cash to Total Assets
Profitability - Income before extraordinary items to Total Assets
Leverage - Total Liabilities to Total Assets
Size - Natural Log of Sales
Qualified Opinion (coded 0 in years of unqualified opinions, otherwise 1)
Lag - Unemployment Rate - 1 year lag
Lag - Prime Rate - 1 year lag

financial distress.

To further refine our analysis, we subdivide the sample into two industry segments. Panel B of table 3 provides results for manufacturing firms and Panel C reports results for wholesale, retail, and service firms. For the financially distressed state, statistically significant variables ($p < 0.05$) for manufacturing firms are Leverage, Qualified Opinion, and Prime Rate, while in Panel C, Size, Qualified Opinion and the Prime Rate are significant for retail firms.

For the bankrupt state, six of seven variables (Profitability, Leverage, Size, Qualified Opinion, Unemployment Rate and the Prime Rate) are significant at $p < 0.05$ for manufacturing firms, while only one of seven (Qualified Opinion) is significant for the retail group. The lack of statistical significance for retail firms is puzzling and suggests further research in industry differences may be fruitful. For example, the significance of Profitability and Leverage for manufacturing firms may reflect their capital intensity and longer receivable collection cycles. Research that expands our knowledge of industry specific characteristics may lead to better explanatory models for bankruptcy and financial distress.

Conclusion

This study examines the use of event history methodology in analyzing financially distressed firms that survive and those that become bankrupt. The advantage of this methodology is that it captures the dynamics of change in financial status and allows for time-varying variables and censored observations. It also allows us to consider both financially distressed and bankrupt firms simultaneously. The use of a dynamic or event history methodology extends prior research which typically uses static analyses or longitudinal approaches based on snap-shots in time.

We estimate model coefficients over the 1977-1987 time period and find that the "transition rate" or dynamic model is useful in identifying significant explanatory variables that differ between financially distressed and bankrupt firms and also between industry classifications. Explanatory variables include financial measures (Liquidity, Profitability, Leverage, Size and Qualified Opinion) and two economic indicators (Unemployment and Prime Rates). We find that both accounting information and economic variables external to the firm are important in explaining the failure process.

Suggestions for Future Research

The results emphasize that further research is needed to understand the characteristics of bankrupt and financially distressed firms. Specifically, additional information about industry differences regarding the failure and recovery processes and how these processes vary in response to changing economic conditions is required. For example, retail firms may not face the same environmental constraints as manufacturing firms and these types of differences need to be recognized in future research models. In addition, consideration of industry specific characteristics may better guide selection of independent variables that explain bankruptcy and financial distress. Finally, the use of a dynamic analysis, which considers data over time and requires no assumptions about the equilibrium of the process, can be especially helpful in times of rapid change.

Footnotes

1. From 1977 to 1987, Dun and Bradstreet report bankruptcy failure rates ranging from 0.24% to 1.20%. These rates are based on all listed concerns (Business Failure Record, 1992).
2. See, for example, Zmijewski (1984), Koh (1991), Koh (1992), Hsieh (1993) and Stone and Rash (1993).
3. See Manski (1981), Allison (1984), and Yamaguchi (1991) for further discussion of event history analysis.
4. In addition to endnote 3, see Carroll (1983) and Tuma et al. (1984) for further discussion of dynamic analysis.
5. For financially distressed firms, independent variables measure information before, during and after the financially distressed period(s). Independent variables for bankrupt firms encompass the time to bankruptcy.

6. This three year requirement insures that the firms are indeed distressed and not just experiencing some fluke in earnings. Because of this requirement, all firms are stable from 1977-1978.
7. The list of ratios tested includes: Cash to Total Assets, Cash Flow to Total Assets, Current Assets to Current Liabilities, Earnings Before Interest and Depreciation to Total Assets, Long-Term Debt to Shareholder's Equity, Natural Log of Assets, Natural Log of Sales, Shareholder's Equity to Total Liabilities, Sales to Total Assets, Total Liabilities to Total Assets, Earnings Before Interest and Depreciation to Sales.
8. Industry averages were calculated from Compustat data based on three digit SIC codes for each relevant SIC code and year and include all listed firms on the NYSE and AMEX.
9. Although the qualified opinion as coded by Compustat is a general measure, it provides an overall indication of going concern problems.
10. We also considered GNP and CPI. The GNP, however, is highly correlated with the unemployment rate and the CPI does not have a significant impact on the financial state of the sample firms. The unemployment rate and the prime rate, however, are correlated with the firms' financial states and are not highly correlated with each other.
11. Separate model analyses for financially distressed (versus stable) and bankrupt (versus stable) firms, as found in prior research, does not allow for comparison of coefficient magnitudes, only of significance levels.

Appendix

Research Models - Transition Rate and Exponential Dynamic Models

The probability that a firm will occupy a particular state at time t+1 given that firm does not occupy the state at time t is given by:

$$p_{jk}(t_1,t_2)=Prob[Y(t_2)=k|Y(t_1)=j]$$

where:

Y = 0 if the firm is stable, 1 if the firm is financially distressed, and 2 if the firm is bankrupt;

t = time in years;

j, k = 0, 1, 2, the alternative states or dependent variable.

This probability is similar to the choice probability model from cross-sectional analysis. The important difference is that the probability at time t_2, when the event (here, change in financial status) occurs, is conditional upon the state occupied at time t_1.

The dependent variable in event history models is the transition rate, the unobserved rates at which financial distress and bankruptcy occur. The transition rate, r_{jk}, is given by:

$$r_{jk}(t)=\lim_{\Delta t\to 0}[p_{jk}(t,t+\Delta t)/\Delta t]$$

Several classes of dynamic models have been defined which differ in their assumptions about the nature of historical time dependence and distribution of the dependent variable. The model chosen for this analysis allows for changing independent variables and assumes that the transition rate is a log-linear function of the variables. The model stated below specifies how the transition rate depends on the X_i firm characteristics.

$$r(t)=e^{\beta X_i}$$

Where:

r(t) = the transition rate or rate of occurrence of financial distress and bankruptcy;

X_i = vector of time-dependent independent variables measuring firm i's characteristics;

b = parameters of the X variables.

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