Journal of Business Finance & Accounting, 29(3) & (4), April/May 2002, 0306-686X

Predicting Bankruptcy Resolution

Ran Barniv, Anurag Agarwal and Robert Leach*

1. INTRODUCTION AND BACKGROUND

Following bankruptcy filing, financially distressed firms in the U.S. are placed under court supervision, until the bankruptcy is resolved. Filing for corporate bankruptcy is required under Chapter 11 of the 1978 bankruptcy code, where management and owners seek court protection against creditors and other claimants.[1] Usually the court confirms a reorganization or rehabilitation plan following the bankruptcy filing. With the approval of the court, bankruptcy filing of publicly traded firms is finally settled, on the average about 17 months after the filing, in the following three alternative resolutions. Firms are either (i) acquired by other firms or (ii) emerged as independent entities or (iii) liquidated.

Firms filing for bankruptcy share similar characteristics of financial distress and therefore it is difficult to predict the final resolution. For example, prior to filing bankruptcy, most firms disclose declining revenues, total assets, book value of equities and earnings. Thus, we expect that distinguishing between the three post-bankruptcy filing outcomes is more difficult than discriminating between sound and financially distressed firms, which has been extensively examined in prior literature.

The purpose of this paper is to classify and predict the final bankruptcy resolution. This research issue has not been examined in prior accounting and finance literature. We develop

* The authors are respectively from Kent State University, the University of Florida and the University of South Carolina at Aiken. They acknowledge the helpful comments of an anonymous referee and an Executive Board referee. Robert Leach provided extensive data collection efforts. (Paper received January 2000, revised and accepted February 2001)

Address for correspondence: Ran Barniv, Graduate School of Management, College of Business Administration, Kent State University, Kent, Ohio, USA.
e-mail: rbarniv@bsa3.kent.edu

a classification and prediction model using logistic regression to classify and predict firms as acquired, emerged or liquidated (a three-group resolution) and also as 'acquired or emerged' versus liquidated (a two-group resolution). A ten-variable logistic regression model is developed employing financial accounting data and non-financial data.[2] The model includes five accounting variables and five non-accounting variables used by bankruptcy courts. Accounting variables include, among others, profitability ratio and a proxy for size. Court related non-financial accounting variables include resignation of top executives, fraud and other characteristics. While the study focuses on classification and prediction provided by the ten-variable model, some discussion of the role of accounting and non-accounting variables is also provided.

From the perspectives of investors, creditors and other stakeholders it is important to predict the outcome following bankruptcy filing. Our preliminary results suggest that investors in filing firms lose significant market values from sixty days prior to filing through one trading day after the filing. More importantly, following the filing, investors in acquired and emerged firms experience significant positive returns between the filing and final resolution, whereas investors in liquidated firms sustain significant additional negative returns. For example, cumulative abnormal returns (CARs) for investors in acquired and emerging firms are, on the average, 155 percent and 137 percent, respectively, from filing through the final court resolution. CARs for liquidated firms, on the other hand, are on average negative 11 percent. Therefore, the three resolutions are ordered based on the returns to investors as acquired (best), emerged (medium) and liquidated (worst). Since liquidation generates negative CARs from filing through the final resolution while acquisition and emergence generate positive CARs, we also examine a two-group resolution of acquired or emerged vs. liquidated firms. Other methods of calculating returns including buy-and-hold returns provide the same ordering, though different magnitudes of return.[3] It is therefore economically desirable to predict the post bankruptcy resolution event.

We use the entire list of firms filing for Chapter 11 between 1980 and 1995, provided by the Securities and Exchange Commission (SEC) to generate our sample. From this list, 237 publicly traded firms, for which the final bankruptcy resolution is already known, have complete financial accounting information, non-financial court-related data and securities prices are selected. For measuring classification and prediction accuracy we use rate of correct classification and also briefly examine the expected cost of misclassification (ECM).

The ten-variable logistic regression model performs quite well in both classification and prediction tasks. For the entire sample, the three-group classification accuracy is about 62 percent using the Lachenbruch (1967) technique, while for a time-series holdout sample, the classification accuracy is about 49 percent. These classification accuracies are significantly better than that expected from random classification.[4]

Some supplemental results suggest that a five-variable non-accounting model performs slightly better than a five-variable accounting model. Further, the classification accuracy and the ECM of the ten-variable model are better than those of both the five-variable models. These results indicate that financial statement data alone is not adequate, and researchers as well as external users of accounting data would benefit from using non-financial accounting information for classifying and predicting bankruptcy resolution.[5]

The remainder of this paper is organized as follows. In Section 2, we provide a brief literature review and discuss our incremental contribution. In Section 3 we present the research methodology which includes a discussion of ordered logistic regression and classification accuracies. Data, sampling and variable selection are described in a subsequent section, followed by a section on empirical results. The summary and conclusions section also includes a discussion of the public policy implications of our results to investors, bankruptcy courts and other stakeholders.

2. PRIOR LITERATURE AND INCREMENTAL CONTRIBUTION

Prior studies have focused on classifying and predicting financial distress or the event of filing bankruptcy. Those studies focus on two-group classification namely healthy versus financially distressed firms. Numerous accounting and finance studies have been published since the pioneering article by Altman (1968). Subsequent early articles use primarily multiple discriminant analysis (MDA) for predicting bankruptcy. Later studies use logit (e.g., Ohlson, 1980), or probit (e.g., Zmijewski, 1984) for predicting financial distress.[6]

Recent studies examine various issues related to predicting financial distress and bankruptcy filing. For example, Richardson et. al. (1998) examine the impact of recession on the prediction of corporate failure. Ward and Foster (1997) use loan default/ accommodation as a response measure for financial distress. Akhigbe and Madura (1996) examine the intra-industry effect on voluntary corporate liquidations. Platt et. al. (1994) examine bankruptcy discrimination with real variables. Hsieh (1993) discusses optimal cutoff points in bankruptcy prediction models. Other aspects of bankruptcy prediction and related issues are also discussed (Ro et al., 1992; Tennyson et al., 1990; and Platt and Platt, 1990). Measuring the classification accuracy has been the primary issue in these and many other studies (e.g., Dopuch et al., 1987; and Liang et al., 1992). Lau (1987) and Ward (1994) develop, respectively, five-state and four-state models of financial distress prior to filing. Recently Laitnen and Laitnen (1998) and Dhumale (1998) use logistic regressions with cash management model and earning retention, respectively, to predict corporate failure. Lennox (1999) discusses the impact of the audit report on bankruptcy prediction. None of these studies have examined post-bankruptcy resolution.

Only a few studies directly explore aspects of the post-bankruptcy scenario. LoPucki (1983) uses a small sample of bankrupt firms to examine the outcome of bankruptcy reorganization using only correlation analyses. Lehavy (1999) examines reporting discretion and fresh start values for firms emerging from bankruptcy. White (1983 and 1989) analyzes the confirmation decision through modeling a coalition of creditors and equity holders. Casey et. al. (1986) uses only accounting variables to discriminate between a group of liquidated firms and a group of restructured firms. Kim and Kim (1999) use a similar two-group analysis applied to Korean firms.

Recent studies examine other aspects of post-bankruptcy filing (e.g., Morse and Shaw, 1988; and Hotchkiss, 1995). However, classification and prediction of the final outcome have not been examined in this prior accounting and finance literature. Our study differs from the earlier literature by focusing explicitly on the classification and prediction of the post bankruptcy resolution event using accounting and non-accounting variables available at the beginning of the bankruptcy filing period. Such predictions may be very relevant for investors in developing investment strategies in bankrupt firms. Creditors and other claimants would also benefit by being able to develop appropriate strategies during the prolonged court deliberations. Bankruptcy judges may also use these predictions as preliminary indicators of the potential future outcome. These and other public policy implications of our approach are discussed in the summary and conclusion section.

3. RESEARCH METHODOLOGY

(i) Ordered Logistic Regression

Most recent studies use and compare multiple techniques for classification such as logit, MDA and Neural Networks (NN). For example, Ohlson (1980), Lo (1986) and Maddala (1991) provide discussions on logit models and comparisons with other techniques. For our study, we use logistic regression, which has been the most commonly used technique in recent literature.[7] We use ordered logistic regressions (Maddala, 1983 and 1991) which fit the ranking of the final resolution (the dependent variable) in ordered ranking of final resolution. As discussed in the introduction, acquired is a better state than emerged, which in turn, is better than a liquidated state. Therefore an ordered logit, which has the following cumulative logistic function is used:

$$P(r|\mathrm{BF}) = F(\alpha_r + X'\beta) = \frac{1}{1 + e^{-(\alpha_r + X'\beta)}},$$

where $r = 1, 2$ and 3 for the three group resolutions and 1and 2 for two-group resolutions; $\alpha 3 > \alpha 2 > \alpha 1 = 0$, $X'\beta$ is the vector of coefficients multiplied by the vector of variables, and $P(r|\mathrm{BF})$ is the conditional probability of the resolution, given that a firm filed for bankruptcy.

(ii) Classification Accuracies

Different cutoff points have been used in prior studies for measuring classification and prediction accuracy. For example, Altman (1968) and Deakin (1972) use cutoff points which minimize misclassification accuracy and Ohlson (1980) and Palepu (1986) use the optimal cutoff points where the distributions of the two groups intersect. For classification and prediction purposes we use cutoff points that minimize the number of misclassifications. The classification accuracy is examined on the full sample using the Lachenbruch (1967) U-technique. This method holds out one observation at a time, estimates the multivariate function with the rest of the observations, and then classifies the holdout observation. This classification is repeated until all observations are classified. In addition, classification accuracy is also examined on an inter-temporal split basis using an estimation sample data drawn from earlier years and a holdout sample with data from subsequent years. The cutoff points, which minimize the number of misclassifications for the estimation sample are used to determine the classification accuracy in the holdout sample (Dopuch et al., 1987).

Several studies use the cutoff points that minimize the ECM (Frydman et al., 1985) because misclassifying firms of different groups may have different costs. A general ECM for more than two-state is presented as follows:

$$\mathrm{ECM} = \sum_{r=1}^{k} P_r C_{q|r} \frac{n_r}{N_r}$$

where, r is any type of resolution, q is a set of all resolutions not equal to r, n_r is the number of firms misclassified for r^{th} resolution. N_r is the sample size for the r^{th} resolution. P_r is the prior probability of resolution r and $C_{q|r}$ is the cost of misclassifying an observation belonging to group r into group q.

For the three-group resolution, a simplified equation is:

$$\mathrm{ECM} = P_1 C_{2,3|1} \frac{n_1}{N_1} + P_2 C_{1,3|2} \frac{n_2}{N_2} + P_3 C_{1,2|3} \frac{n_3}{N_3},$$

where n_i is the total number of type i misclassifications; N_i is the sample size of the i^{th} state, $i = 1, 2$ and 3 in this study; P_i equals the prior probability for state i and $\mathrm{C}_{..|i}$ equals the cost of misclassification of an observation belonging to group i. This equation can be further simplified for any two-group resolution. Empirical analysis indicates that an investment of $100 in a filing firm, one day after filing, returns over $200 for firms that were eventually acquired or emerged and about $80 for liquidated firms. Given these results, misclassifying a liquidated firm is approximately three times more costly than misclassifying acquired or emerged firms. Therefore we use $C_{2,3|1} = C_{1,3|2} = 1$ and $C_{1,2|3} = 3$, which is also confirmed by the CARs reported in the introduction.

4. DATA SAMPLING AND VARIABLES

(i) Sampling

We obtain the list of all publicly traded firms which filed bankruptcy from 1980 through 1995 from the Office of the General Counsel of the SEC. However, we use only those firms that filed for bankruptcy prior to 1992 because some firms remained under bankruptcy court supervision for over six years. All companies which operate in regulated industries, such as financial institutions, and some other types of firms are excluded.[8]

A sample of 237 publicly traded firms with complete accounting data, price data, and court-related data is used. Table 1 shows the distribution of the firms by industry. The majority of the companies are manufacturing firms (99) and wholesale and retail firms (61) which comprise 42 percent and 26 percent of the sample, respectively. Data are obtained from COMPUSTAT and supplemented from annual reports and 10-Ks available on microfilm. Prices are obtained from the CRSP and are extended using data provided by Wheat-First-Butcher-Singer for firms traded in regional exchanges. Additional court related data are obtained using *Lexis/Nexis*, *Moody's Industrial Report*, *Wall Street Journal* and *Commerce Clearing House's Capital Change Reporting*.

The 237 filing firms include 49 (21 percent) acquired firms, 119 (50 percent) emerged firms, and 69 (29 percent) liquidated firms. We analyze the final bankruptcy resolutions for the entire population of all publicly traded firms that filed for bankruptcy

Table 1

The Sample of Bankrupt Firms

Industry (two digit SIC code)	*Bankruptcy Resolution* Acquired	*Emerged*	*Liquidated*	*All Firms*
Agriculture, Mining and Construction (01–19)	7	24	7	38 (16%)
Manufacturing (20–39)	20	46	33	99 (42%)
Wholesail and Retail (50–59)	12	29	20	61 (26%)
Other Industries (40–46, 70–89)	10	20	9	39 (16%)
Total Firms	49 (21%)	119 (50%)	69 (29%)	237 (100%)

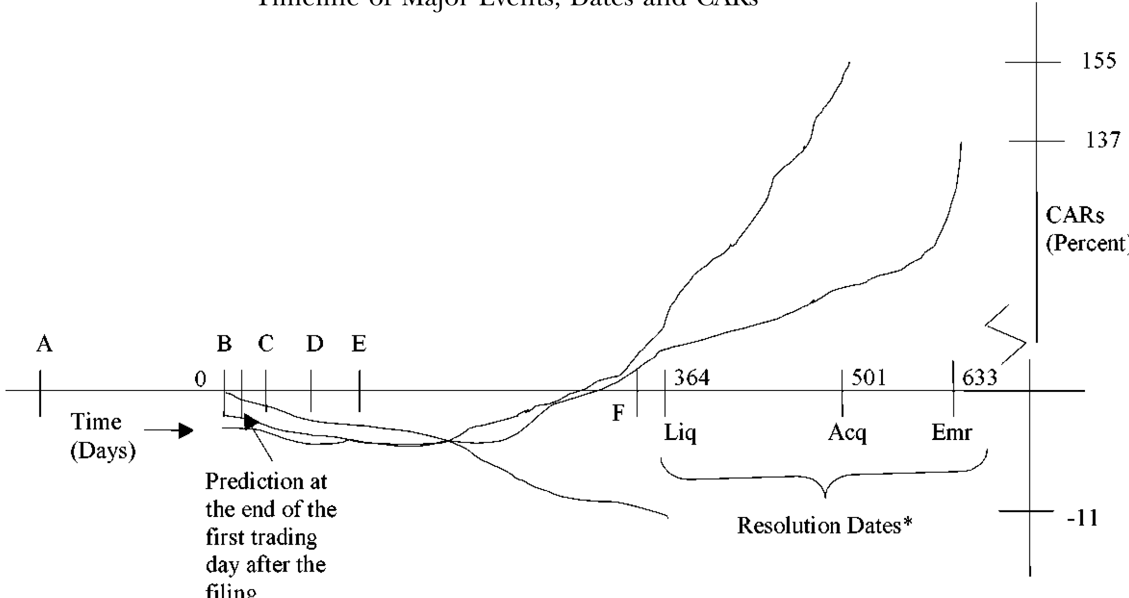
between 1980 and 1992 obtained from the SEC. The proportions of firms for the three resolutions in the entire population are similar to the proportions in our sample. This full sample is used to predict the final resolution at the first day after the filing. The firms are further split into estimation and holdout samples. The estimation sample includes 114 firms that filed for bankruptcy from 1980 through 1986. The holdout sample includes 123 firms that filed bankruptcy from 1987 through 1991.

(ii) Background

Before we discuss the variables it is important to understand the sequence of events during the post-filing period because some of the variables affect the specific events and are used by various stakeholders throughout the bankruptcy process. For example, holders of secured debt may oppose reorganization and promote liquidation. A timeline of major events is depicted in Figure 1, along with dates and CARs. The filing of Chapter 11 petition date is usually followed by a filing of a schedule of assets and liabilities with the court. This process is followed by bar deliberations where creditors must file a proof of claim on the bar date. The next important date is the filing of a reorganization plan, which is followed by hearing and disclosure statements and a final voting on the plan, confirmation hearing and final confirmation. If the

Figure 1

Timeline of Major Events, Dates and CARs



Notes:
A: Annual Report and/or 10-K release
B: Filing Day
C: Filing Schedule of Assets and Liabilities
D: Filing a proof of claim at the bar date
E: Filing Reorganization Plan
F: Confirmation Date
*: The average duration between filing and resolution.

reorganization plan is not confirmed, the bankruptcy judge can rule to transfer the firm to liquidation under Chapter 7. However, if organization continues, two major events may occur. The firm may exit the bankruptcy process and emerge as a new entity or it may be acquired by another firm.

We use the filing date and the final resolution date as the major useful events. The duration between filing and final resolution is, on the average 364 days for liquidated firms, 501 days for acquired firms, and 633 days for emerged firms. Classification and prediction is done at the end of the first trading day after the filing using financial and non-financial data available to the court and to investors at that day. The CARs obtained from filing through the final resolution are also presented. The CARs for the acquired firms are higher than those for emerged firms and the CARs for the liquidated firm are negative and decrease between bankruptcy filing and the final resolution event. These results further illustrate the differences between the three groups. As explained before, Figure 1 provides some background for the variable selection process described below.

(iii) Variable Selection

To select financial accounting characteristics, we examine variables used in three previous studies for predicting bankruptcy (Altman, 1968; Ohlson, 1980; and Frydman et al., 1985). Intuitively, these variables would be useful for predicting the final resolution. Therefore our initial set includes these variables. We apply the following variable selection process for these variables. First, a sample of more than 3000 healthy firms and our 237 filing firms is used to examine the significance levels of the estimated coefficients and the classification accuracies using the obtained variables of each of these three models separately. The results (not reported) demonstrate that all variables included in each of these three studies perform reasonably well for predicting the bankruptcy filing. However, in contrast, univariate analysis of the variables and logistic regressions based on these three studies suggest that all but two of these variables are not statistically significant for predicting the final resolution. Only the firm size (LNTA) and Net Income to Total Assets (NI/TA), are found to be somewhat significant for various three groups or two sub-group classifications. Therefore, in search for additional relevant variables, we scrutinize more than twenty five accounting and non-accounting court-related characteristics that have been used in practice by bankruptcy judges and attorneys.[9]

A three step analysis is used for selecting the additional variables. First, we conduct correlation analysis and for variables that are highly correlated with one another, only one variable is selected. Second, we use univariate analysis to exclude variables which did not differ significantly across the three resolutions. Third, for the remaining variables, we use logit analyses on all possible two and three groups to test the significance of these variables and select five accounting variables and five non-accounting variables that are statistically significant in at least one combination. Since liquidation is the worst scenario and acquisition is the best, we define the dependent variable: resolution as 0,1 and 2 for acquired, emerged and liquidated firms, respectively. The following ten variables are used in this study.

(a) Five Financial Accounting Variables

NI/TA = Net Income/Total Assets. This variable is used by Ohlson (1980) and other studies. We expect a negative estimated coefficient in the logistic regression since as this variable increases, the probability of liquidation decreases.

LNTA = The natural logarithm of (Total Assets/GDP deflator). This variable is a proxy for firm size and is suggested by Ohlson (1980). We expect a negative estimated coefficient in the logistic regression since as size increases, the probability of liquidation decreases.

INTA/S = Intangible Assets/Net Sales. We expect a negative estimated coefficient in the logistic regression since as intangible assets increase, the firm becomes a more attractive target for acquisition.

TD/TL = Interest Bearing Debt/Total Liabilities. We expect a positive estimated coefficient in the logistic regression since as this variable increases, the probability of liquidation increases.

SED/TD = Secured Interest Bearing Debt/Total Liabilities. We expect a positive estimated coefficient in the logistic regression since as this variable increases, the probability of liquidation also increases because a secured-debt claimant would tend to promote liquidation.

(b) Five Non-Financial Accounting Variables

FRAUD = Fraudulent Activity (1 if fraud is reported, 0 otherwise). We expect a positive estimated coefficient in the logistic regression since as this variable increases, the probability of liquidation increases.

RESN = Resignation by Top Management (1 if resignation of top management is reported, 0 otherwise). We expect a negative estimated coefficient in the logistic regression, since increase in this variable implies new management, which would decrease the probability of liquidation.

C-DEBT = The number of major classes of bond holders. Based on the univariate analysis, we expect a negative estimated coefficient in the logistic regression since as the number of classes of bond holders increases, the probability of liquidation decreases.

H-H INDX = Herfindahl-Hirchman Index of competition. The index varies between 0 and 1. We expect a positive estimated coefficient in the logistic regression since as this variable increases, the probability of liquidation increases because there is more competition in the industry.

PLOSS = Price weighted CARs from 60 days prior to filing through one day after the filing. We expect a negative estimated coefficient in the logistic regression since as this variable increases (i.e., more positive or less negative returns), the probability of liquidation decreases. Since market prices for several bankrupt firms are very low, the CAR for each firm is weighted by a compound price change index, suggested by Mikkelson and Ruback (1985).

5. EMPIRICAL RESULTS

(i) Univariate Analyses

Table 2 presents univariate comparisons and tests of significance for the ten variables used in our analysis. Panel A presents the sample means, Panel B shows the *t*-tests and Panel C exhibits the Wilcoxon *Z*-tests. For the accounting variables, the results suggest that LNTA is significantly larger for acquired and emerged firms compared with liquidated firms. INTA/S is significantly larger for acquired firms. This result is not surprising since more intangible assets makes firms more attractive targets for acquisition. Most of the differences between the other three accounting variables are not statistically significant.

The comparisons of the means for the non-accounting variables are statistically significant for four of the five variables. FRAUD is significantly larger for liquidated firms. C-DEBT is significantly smaller for the liquidated firms. The H-H INDX is significantly greater for the liquidated firms. Liquidated firms demonstrate statistically significant higher PLOSS. The differences across the resolutions for RESGN are statistically insignificant. In sum, acquired firms are medium-size companies, with greater intangible assets. Emerging firms are larger, tend to have less secured debt and more classes of bondholders. Liquidated firms are smaller, tend to have more secured debt and are more subject to fraud.

(ii) Logistic Regressions

Table 3 provides the ten-variable logistic regression results for the entire sample. Two columns are presented in the table. The first column includes all the three groups for the entire sample. The mean estimated coefficients based on the Lachenbruch technique are presented. The second column provides the mean estimated Lachenbruch's coefficients for the two-group model for acquired and emerged vs. liquidated firms. The logistic regressions are highly significant and the Pseudo-R^2 vary between 0.11 and 0.20. The estimated coefficients for LNTA and SED/TD are statistically significant across the two columns. These results indicate that the smaller the firm and higher the proportion of secured debt, the higher the probability that the firm would be

Table 2

Univariate Comparisons of Variables and Tests of Significance

Group	NI/TA	LNTA	INTA/S	TD/TL	SED/TD	FRAUD	RESN	C-DEBT	H-H INDEX	PLOSS
	Variables									
	Accounting Variables					*Non-Accounting Variables*				
Panel A: Sample Means										
Aquired	−0.70	3.68	0.14	0.62	0.28	0.04	0.24	5.10	0.08	−0.483
Emerged	−0.33	3.81	0.03	0.58	0.24	0.06	0.25	5.89	0.10	−0.569
Liquidated	−0.26	2.85	0.04	0.54	0.32	0.28	0.23	3.77	0.10	−0.657
Panel B: t-tests										
Acq v. Liq.	−1.06	2.38[a]	1.59	2.13[b]	−0.73	−3.83[a]	0.16	2.54[a]	−1.45	2.68[a]
Emr v. Liq.	−1.03	3.90[a]	−0.38	1.13	−0.21	−3.71[a]	0.31	4.44[a]	−0.40	2.20[b]
Acq v. Emr	−0.90	−0.41	1.73[b]	1.25	1.03	−0.47	−0.10	−1.28	−1.36	1.34
Panel C: Wilcoxon Z-tests										
Acq v. Liq.	−0.91	3.04[a]	1.85[b]	2.08[b]	−0.69	−3.26[a]	0.16	2.12[b]	−2.81[a]	2.79[a]
Emr v. Liq.	0.21	2.98[a]	0.38	1.19	−1.98[b]	−4.13[a]	0.31	3.43[a]	−5.34[a]	1.97[b]
Acq v. Emr	−0.85	−0.01	1.77[b]	1.28	1.16	−0.47	−0.10	0.86	−2.11[b]	1.17

Notes:
[a] Significant at $p < 0.01$, one-tailed test.
[b] Significant at $p < 0.05$, one-tailed test.

Table 3

Ten-Variable Logistic Regression Estimates for the Entire Sample

	Acq vs. Emr vs Liq	*Acq & Emr vs. Liq*
	*Mean Lachenbruch Estimates**	
Variables		
Intercept 1	2.093	−0.213
	(3.50)[a]	
Intercept 2	−0.549	
	(−0.95)	
NI/TA	0.368	0.689
	(1.10)	(1.53)
LNTA	−0.230	−0.314
	(2.28)[b]	(−2.33)[b]
INTA/S	−1.414	−0.744
	(−2.03)[b]	(−0.85)
TD/TL	−1.548	−1.175
	(−2.07)[b]	(−1.22)
SED/TD	1.157	1.671
	(1.91)[b]	(2.17)[b]
FRAUD	1.864	1.987
	(3.94)[a]	(3.80)[a]
RESN	−0.669	−0.740
	(−2.07)[b]	(−1.72)[b]
C-DEBT	0.016	−0.109
	(0.36)	(−1.47)
H-H INDEX	3.381	3.500
	(1.78)[b]	(1.49)
PLOSS	−1.118	−1.350
	(−2.48)[a]	(−2.03)[b]
Log-likelihood χ_2	54.50[a]	57.48[a]
Pseudo-R^2	0.111	0.201
Somers D	0.418	0.586

Notes:
* The mean Lachenbruch estimated coefficients yield similar coefficients to those based on logit model for the entire sample (without repetitions).
t-tests are in parentheses.
[a] Significant at $p < 0.01$, one-tailed test.
[b] Significant at $p < 0.05$, one-tailed test.

liquidated. The estimated coefficients for NI/TA are not statistically significant. The two remaining accounting variables have significant estimated coefficients only for the three-group analysis.

Among the non-accounting variables, the estimated coefficients for FRAUD are highly statistically significant. For example, for the three-group column, the *t*-test is 3.94 and for the acquired and emerged versus liquidated, it is 3.80. The estimated coefficients of RESN and PLOSS are also statistically significant across the two columns. The estimated coefficients of H-H INDX are significant in the first column and the estimated coefficients for C-DEBT are not statistically significant.

Table 4 presents similar results for the within estimation sample described in Section 4 *(i)*. The models are highly significant and the Pseudo-R^2 are 0.14 and 0.28 for the three groups and two groups, respectively. Again, the estimated coefficients for FRAUD are highly statistically significant for the two sub-groupings. Estimated coefficients of several other variables such as NI/TA, TD/TL and H-H INDX are not statistically significant.

(iii) Classification and Prediction Accuracies

Panel A of Table 5 shows the percentage of classification accuracy using the ten-variable model for the entire sample based on the Lachenbruch technique. The overall classification accuracies are 61.6 percent for the three groups and 75.1 percent for the two groups. These results are significantly higher than a proportionate three-group (two-group) random classification of 38.0 (58.7) percent.[10] Further, classification accuracies are reported for each resolution. Note that the classification accuracies for the emerged and liquidated firms are reasonably high but the accuracy is relatively low for the acquired firms. Interpretations of these results are limited because the cutoffs are based on minimizing the overall number of misclassifications and not classification accuracies for each group.

The next section of Panel A shows the prediction accuracy for the holdout sample. The cutoff points that minimize misclassification in the estimation sample are used to classify observations in the holdout sample. The three-group and the two-group prediction accuracies are 48.8 percent and 69.9 percent, respectively, significantly better than the proportionate chance predictions of 37.5 and 54.1 percent.

Panel B of Table 5 shows that the five variable non-accounting model provides better classification than the five-variable

Table 4

Ten-Variable Logistic Regression Estimates for the Estimation Sample

	Acq vs. Emr vs Liq	*Acq & Emr vs. Liq*
Variables		
Intercept 1	2.491	−0.318
	(2.73)[a]	(−0.25)
Intercept 2	−0.510	
	(−0.58)	
NI/TA	0.098	0.118
	(0.20)	(0.16)
LNTA	−0.413	−0.395
	(−2.73)[a]	(−1.57)
INTA/S	−5.609	−17.322
	(−1.22)	(−1.65)
TD/TL	−1.773	−1.949
	(−1.64)	(−1.25)
SED/TD	1.418	2.452
	(1.64)	(1.88)[b]
FRAUD	2.696	3.421
	(3.42)[a]	(3.27)[a]
RESN	−0.563	−1.225
	(−1.03)	(−1.37)
C-DEBT	0.116	−0.081
	(1.68)[b]	(−0.67)
H-H INDEX	1.141	2.429
	(0.39)	(0.59)
PLOSS	−0.572	−1.190
	(−0.71)	(−0.98)
Log-likelihood χ_2	32.14[a]	33.19[a]
Pseudo-R^2	0.140	0.283
Somers D	0.467	0.686

Notes:
t-tests are in parentheses.
[a] Significant at $p < 0.01$, one-tailed test.
[b] Significant at $p < 0.05$, one-tailed test.

accounting model. Panels A and B demonstrate that for the entire sample the classification accuracies of the ten-variable model tend to be better than those for the five accounting variables and five non-accounting variables models.

Table 6 shows the results of ECMs for the entire sample and the holdout sample. The results demonstrate that the ECM for

Table 5

Percentages of Correct Classification Using Logistic Regressions

Model	*Acquired* %	*Emerged* %	*Liquidated* %	*Acq & Emr* %	*All Firms* %
Panel A: The Ten-Variable Model					
The Entire Sample[a]					
Three-Group Classifications	12.2	82.3	60.8		61.6
Acquired and Emerged vs. Liquidated			56.6	82.7	75.1
The Holdout Sample[b]					
Three-Group Classifications	27.3	63.2	40.9		48.8
Acquired and Emerged vs. Liquidated			27.3	93.7	69.9
Panel B: Three-Group Accounting Versus Non-Accounting Models					
The Entire Sample[a]					
Five-Variable Accounting Model	10.2	67.2	42.1		48.2
Five-Variable Non-Accounting Model	12.2	75.6	50.7		55.3
The Holdout Sample[b]					
Five-Variable Accounting Model	27.3	61.4	38.7		47.2
Five-Variable Non-Accounting Model	36.4	66.7	43.2		52.8

Notes:
[a] The percentages reported are based on cutoff points that minimize the total number of misclassifications for all firms in the sample based on the Lachenbruch technique.
[b] Cutoff points that minimize the number of misclassifications in the estimation sample are used to predict classification accuracy in the holdout sample.

acquired and emerged vs. liquidated is significantly lower (i.e., better) than that for the three groups. In addition, the ECMs for the five-variable non-accounting models tend to be better than those for the five-variable accounting model. Further comparisons across the models for the holdout sample indicate that ECMs for the ten-variable models tend to be lower (better) than the ECMs for the five-variable models, except for the ten-variable model for the three-group classification. Thus, the results reported in Tables 5 and 6 suggest that non-accounting

Table 6

Expected Cost of Misclassification (ECM)

Model	*Entire Sample*[a]	*Estimation Sample*[b]	*Holdout Sample*[b]
Panel A: The Ten-Variable Model			
Three-Group Classifications	0.6118	0.5526	0.9349
Acquired and Emerged vs. Liquidated	0.5020	0.4511	0.6801
Panel B: Three-Group Accounting Versus Non-Accounting Models			
Five-Variable Accounting Model	0.8607	0.7980	0.8790
Five-Variable Non-Accounting Model	0.7163	0.7456	0.8618

Notes:
[a] The ECMs are based on Lachenbruch classifications reported in Table 5.
[b] Cut-off points used for the estimation and holdout sample are based on those that minimize the ECMs in the estimation sample. Therefore, results for the estimation sample are also reported.

information improves the predictive ability of the final resolution given that accounting information is already included in the model.

6. SUMMARY AND CONCLUSIONS

This study classifies and predicts the court resolution following bankruptcy filing. Prior studies concentrate on predicting the bankruptcy filing event or discriminating between healthy and financially distressed firms. About 17 months, on an average, following the bankruptcy filing event, US bankruptcy courts confirm one of three possible final resolutions, namely, acquisition, emergence or liquidation. Classifying and predicting the final resolution is more difficult than discriminating between healthy and bankrupt firms because all filing firms are already in financial distress. It is important to predict the final resolution because of the substantial economic consequences to different stakeholders. For example, investors in liquidated firms sustain significant losses prior to filing and from filing through the final resolution. Whereas, investors in acquired and emerged firms gain significant positive returns from the filing date through to the final resolution, after sustaining negative returns prior to filing.

We use a sample of 237 firms of which 49 were acquired, 119 emerged from bankruptcy and 69 were liquidated. Logistic regression is used to classify and predict the final resolution for the three groups, namely, acquired, emerged and liquidated and two groups, namely, acquired and emerged vs. liquidated. A ten-variable model, which includes five accounting and five non-accounting variables, performs quite well, correctly classifying 61.6 percent of all firms in their respective three groups and correctly classifying 75.1 percent of the firms in the two-group setting. These classification accuracies are based on the Lachenbruch U-technique. In addition, an inter-temporal split of the sample to an estimation sample and a holdout sample is performed. The classification accuracies for the holdout sample are 48.8 percent for the three groups and 69.9 percent for the two groups.

There are several implications of this study for investors and other stakeholders. The suggested models are useful for investors in predicting the final resolution of the bankruptcy process. These predictions are helpful for investment strategies in filing firms. Creditors and other claimants may utilize the models while negotiating the terms of the reorganization for filing firms. Predicting the resolution would help bankruptcy judges in making decisions about the final resolution. Auditors may use the predictions when considering a going-concern or similar qualification. Future research may examine these and other discriminating variables for developing better predictions of the final resolution. In addition, the better ability to predict the final resolution could potentially reduce the bankruptcy costs, shorten the reorganization process, and provide better control for the various key stages during the bankruptcy process.

We find that only a few of the accounting variables used in prior literature for predicting financial distress or bankruptcy filing are useful for predicting the final bankruptcy resolution event. Non-accounting variables such as fraud, resignation of executives, and investors' past losses seem to be more useful for investors, creditors and bankruptcy judges in predicting the post-filing resolution. This relates to another important public policy issue of the relevancy of accounting disclosure. The study indicates that increasing non-accounting disclosure in financial statements may benefit the stakeholders of bankrupt firms. For example, disclosing non-accounting items in notes to annual reports, petitioning reports and plan confirmation reports may improve the information provided to various stakeholders. In sum, it appears that greater and better accounting and non-accounting disclosure may be necessary to provide external users with relevant information for ascertaining the likely outcome of Chapter 11 filing *ex ante*.

NOTES

1 Chapter 11 of the Bankruptcy Reform Act (1978) allows the court to extend the longevity of the reorganization. Bankruptcy court may convert the firm from chapter 11 to liquidation under chapter 7.

2 Classification refers to entire sample using the Lachenbruch technique whereas prediction refers to the holdout sample.

3 Holdout returns from the filing through the final resolution were moderately positive for acquired firms and slightly lower but positive for emerging firms and moderately negative for liquidated firms.

4 Given the composition of the sample, the expected value of classification accuracy for random sampling without replacement, would be 38 percent for the three-group resolution.

5 In a different context, this finding is similar to results presented by Amir and Lev (1996) who find that non-accounting data are more relevant than accounting data for evaluation of the fast growing wireless communication firms.

6 Early studies by Altman (1968), Deakin (1972), Edmister (1972) and Blum (1974) used MDA to predict and classify bankruptcies. More recent studies used logit or probit models to predict bankruptcy (Ohlson, 1980; Zmijewski, 1984; Zavgren, 1985; Burgstahler et el., 1989; Barniv, 1990; and Gilbert et al. 1990). Studies also concentrate on selecting financial variables and comparing estimation procedures for predicting bankruptcy (Frydman et al., 1985; Palepu, 1986; and Tam and Kiang, 1992). Taffler (1984) and Keasey and McGuinness (1990) examine financial distress in the UK while Micha (1984) and Skogsvik (1990) examine business failures in France and Sweden, respectively. Altman (1984) provides a review of failure prediction models in various countries.

7 Alternative techniques such as Nonparametric Discriminant Analysis (NPDA) described by Barniv and Raveh (1989), and NN described for example, by Tam and Kiang (1992), are also utilized but the results are less defensible so they are not reported here. For instance, Trigueiros and Taffler (1996) demonstrate some inappropriateness of such intensive computer algorithms for statistical analysis of this nature.

8 We exclude utility, railroad, health-care, trucking and other transportation and other regulated industries such as financial institutions including banks, insurance companies, mortgage and thrift institutions. We exclude these firms because the bankruptcies are handled differently for these industries. Firms that filed for bankruptcy more than once and companies which initially filed for Chapter 7 are also excluded.

9 The list of scrutinized variables includes some characteristics mentioned in prior bar deliberations and by other sources such as Dun and Bradstreet. Ten of these variables are included in our final analysis. Our analysis excludes variables such as firm age, ownership concentration, debt-maturity dates, which are eliminated through the selection process described in the next paragraph.

10 The proportionate random (chance) criterion for the entire sample is $(49^2 + 119^2 + 69^2)/237^2 = 0.380$ for the three-group classification and $(168^2 + 69^2)/237^2 = 0.587$ for the two-group classification.

REFERENCES

Akhigbe, A. and J. Madura (1996), 'Intra-Industry Effects of Voluntary Corporate Liquidations', *Journal of Business Finance & Accounting*, Vol. 23 (September), pp. 915–30.

Altman, E.I. (1968), 'Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy', *The Journal of Finance*, Vol. 23 (September), pp. 589–609.

__________ (1984), 'The Success of Business Failure Prediction Models: An International Survey', *Journal of Banking and Finance*, Vol. 8 (June), pp. 171–98.

Amir, A. and B. Lev (1996), 'Value-Relevance of Non-financial Information: The Wireless Communication Industry', *Journal of Accounting and Economics*, Vol. 22 (January), pp. 3–30.

Barniv, R. (1990), 'Accounting Procedures, Market Data, Cash-Flow Figures and Insolvency Classification: The Case of the Insurance Industry', *The Accounting Review*, Vol. 65 (July), pp. 578–604.

__________ and A. Raveh (1989), 'Identifying Financial Distress: A New Nonparametric Approach', *Journal of Business Finance & Accounting*, Vol. 16 (Summer), pp. 361–83.

Blum, M. (1974), 'Failing Company Discriminant Analysis', *Journal of Accounting Research*, Vol. 12 (Spring), pp. 1–25.

Burgstahler, D., J. Jiambalvo and E. Noreen (1989), 'Changes in the Probability of Bankruptcy and Equity Value', *Journal of Accounting and Economics*, Vol. 11 (No. 3), pp. 207–24.

Casey, C., V. McGee and C. Stickney (1986), 'Discriminating Between Reorganized and Liquidated Firms in Bankruptcy', *The Accounting Review*, Vol. 6 (April), pp. 249–62.

Deakin, E. (1972), 'A Discriminant Analysis of Predictors of Business Failure', *Journal of Accounting Research,* Vol. 10 (Spring), pp. 167–79.

Dhumale, R. (1998), 'Earning Retention as Specification Mechanism in Logistic Bankruptcy Models: A Test of the Free Cash Theory', *Journal of Business Finance & Accounting*, Vol. 25 (September/October), pp 1005–24.

Dopuch, N., R.W. Holthausen and R.W. Leftwich (1987), 'Predicting Audit Qualifications with Financial and Market Variables', *The Accounting Review*, Vol. 62 (July), pp. 431–54.

Edmister, R.O. (1972), 'An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction', *Journal of Financial and Quantitative Analysis*, Vol. 7 (March), pp. 1477–93.

Frydman H., E.I. Altman and D. Kao (1985), 'Introducing Recursive

Partitioning for Financial Classification: The Case of Financial Distress', *The Journal of Finance*, Vol. 40 (March), pp. 269–91.
Gilbert, L.R., K. Menon and K.B. Schwartz (1990), 'Predicting Bankruptcy for Firms in Financial Distress', *Journal of Business Finance & Accounting*, Vol. 17, No. 1 (Spring), pp. 161–71.
Hotchkiss, E.S. (1995), 'Postbankruptcy Performance and Management Turnover', *Journal of Finance*, Vol. 50 (March), pp. 3–21.
Hsieh, S.J. (1993), 'A Note on the Optimal Cutoff Point in Bankruptcy Prediction Models', *Journal of Business Finance & Accounting*, Vol. 20 (April), pp. 457–64.
Keasey, K. and P. McGuinness (1990), 'The Failure of UK Industrial Firms for the Period 1976-1984, Logistic Analysis and Entropy Measure', *Journal of Business Finance & Accounting*, Vol. 17 (Spring), pp. 119–35.
Kim, M. and M. Kim (1999), 'A Note on the Determinants of the Outcomes of Bankruptcy Petitions: Evidence From Korea', *Journal of Business Finance & Accounting*, Vol. 26 (September/October), pp. 997–1011.
Lachenbruch, P.A. (1967), 'An Almost Unbiased Method for Obtaining Confidence Intervals for the Probability of Misclassification in Discriminant Analysis', *Biometrics*, Vol. 23 (December), pp. 639–45.
Laitnen, E.K. and T. Laitnen (1998), 'Cash Management Behavior and Failure Prediction', *Journal of Business Finance & Accounting*, Vol. 25 (September/October), pp. 843–920.
Lau, A. Hing-Ling (1987), 'A Five-State Financial Distress Prediction Model', *Journal of Accounting Research*, Vol. 25 (Spring), pp. 127–38.
Lennox, C.S. (1999), 'The Accuracy and Incremental Information Content of Audit Reports in Predicting Bankruptcy', *Journal of Business Finance & Accounting*, Vol. 26 (June/July), pp. 757–778.
Liang,T.P., J.S. Chandler, I. Han and J. Roan (1992), 'An Empirical Investigation of Some Data Effects on the Classification Accuracy of Probit, ID3, and Neural Networks', *Contemporary Accounting Research*, Vol. 9 (Spring), pp. 306–28.
LoPucki, L.M. (1983), 'The Debtor in Full Control-System Failure Under Chapter 11 of the Bankruptcy Code?', *American Bankruptcy Law Journal*, pp. 99–126.
Maddala, G.S. (1983), *Limited Dependent and Qualitative Variables in Econometrics* (Cambridge University Press, Cambridge).
__________ (1991), 'The Perspective on the Use of Limited-Dependent and Qualitative Variables Models in Accounting Research', *The Accounting Review*, Vol. 66 (October), pp. 788–807.
Micha, B. (1984), 'Analysis of Business Failure in France', *Journal of Banking and Finance*, Vol. 8 (June), pp 281–92.
Mikkelson, W.H. and R.S. Ruback (1985), 'An Empirical Analysis of the Interfirm Equity Investment Process', *Journal of Financial Economics*, Vol. 14 (No. 4), pp. 523–53.
Morse, D. and W. Shaw (1988), 'Investing in Bankrupt Firms', *Journal of Finance*, Vol. 43 (December), pp. 1193–206.
Ohlson, J.A. (1980), 'Financial Ratios and the Probabilistic Prediction of Bankruptcy', *Journal of Accounting Research*, Vol. 18 (Spring), pp. 109–31.
Palepu, K.G. (1986), 'Predicting Takeover Targets: A Methodological and Empirical Analysis', *Journal of Accounting and Economics*, Vol. 8, No. 1, pp. 3–35.
Platt. H.D. and M.B. Platt (1990), 'Development of a Class of Stable Predictive

Variables: The Case of Bankruptcy Prediction', *Journal of Business Finance & Accounting*, Vol. 17 (Spring), pp. 31–51.

Platt, H.D., M.B. Platt and J.G. Pedersen (1994), 'Bankruptcy Discrimination with Real Variables', *Journal of Business Finance & Accounting*, Vol. 21 (June), pp. 491–510.

Richardson, F.M, G.D. Kane and P. Lobingier (1998), 'The Impact of Recession on the Prediction of Corporate Failure', *Journal of Business Finance & Accounting*, Vol. 25 (January/March), pp. 167–86.

Ro, B.T., V. Zavgren and S.J. Hsieh (1992), 'The Effect of Bankruptcy on Systematic Risk of Common Stock: An Empirical Assessment', *Journal of Business Finance & Accounting*, Vol. 19 (April), pp. 309–28.

Skogsvik, K. (1990), 'Current Cost Accounting Ratios as Predictors of Business Failures: The Swedish Case', *Journal of Business Finance & Accounting*, Vol. 17 (Spring), pp. 137–60.

Taffler, R.J. (1984), 'Empirical Models for Monitoring of UK Corporations', *Journal of Banking and Finance*, Vol. 8 (June), pp. 199–227.

Tam, K.Y. and M.Y. Kiang (1992), 'Managerial Applications of Neural Networks: The Case of Bank Failure Predictions', *Management Science*, Vol. 38 (July), pp. 926–47.

Tennyson, B.M, R.W. Ingram and M.T. Dugan (1990), 'Assessing the Information Content of Narrative Disclosures in Explaining Bankruptcy', *Journal of Business Finance & Accounting*, Vol. 17 (Summer), pp. 391–410.

Trigueiros D. and R. Taffler (1996), 'Neural Networks and Empirical Research in Accounting', *Accounting and Business Research*, Vol. 26, No. 4, pp. 347–55.

Ward, T.J. (1994), 'An Empirical Study of the Incremental Predictive Ability of Beaver's Naíve Operating Flow Measure Using Four-State Ordinal Models of Financial Distress', *Journal of Business Finance & Accounting*, Vol. 21 (June), pp. 547–61.

__________ and B.P. Foster (1997), 'A Note on Selecting a Response Measure for Financial Distress', *Journal of Business Finance & Accounting*, Vol. 24 (July), pp. 869–78.

White, M.J. (1983), 'Bankruptcy Costs and the New Bankruptcy Code', *Journal of Finance*, Vol. 38 (June), pp. 477–87.

__________ (1989), 'The Corporate Bankruptcy Decision', *Journal of Economic Perspectives*, Vol. 3 (Spring), pp. 129–51.

Zavgren, C. (1985), 'Assessing the Vulnerability to Failure of American Industrial Firms: A Logistic Analysis', *Journal of Business Finance & Accounting*, Vol. 12 (Spring), pp. 19–45.

Zmijewski, M.E. (1984), 'Methodological Issues Related to the Estimation of Financial Distress Prediction Models', *Journal of Accounting Research*, Vol. 22 (Spring), pp. 59–82.