Cash Flow Information and the Prediction of Financially Distressed Mining, Oil and Gas Firms: A Comparative Study

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Abstract

This study tests whether cash flow information is more useful to creditors in predicting financially distressed mining, oil and gas firms than it is in predicting financial distress in other industries. The results of this study suggest that cash flows are more useful to creditors in predicting financially distressed mining, oil and gas firms than they are predicting financially distressed firms in other industries. Results also show that different cash flows are useful in predicting financially distressed mining, oil and gas firms than are useful in predicting financially distressed control firms.

Introduction

Previous studies by Beaver (1966), Deakin (1972), Blum (1974), Casey and Bartczak (1984 and 1985), Gentry et al. (1985 and 1987), Aziz et al. (1988), Aziz and Lawson (1989), Gilbert et al. (1990), and Ward (1992) used an ability to predict financial distress criterion to test the usefulness of cash flow information. The accounting information that best distinguishes between distressed and nondistressed companies is considered most useful to creditors. Research results on the predictive usefulness of cash flows have been disappointing for advocates of cash flow information. Researchers have found little evidence supporting the belief that cash flow information has incremental predictor usefulness over accrual information in predicting financial distress. Only cash flow from operating activities is possibly a consistent strong incremental predictor of financial distress.[1]

However, cash flow theory suggests that, even though cash flow from operating activities may be the most important predictor of financial distress, other net cash flows should also have incremental predictive usefulness. Why then have prior financial distress studies failed to show that net cash flows from investing and financing activities are useful in predicting financial distress? One possible explanation is that the usefulness of cash flow information is industry specific.

Cash flows important in predicting financial distress in one industry may not be important in predicting financial distress in another industry. Since previous researchers normally matched healthy and distressed firms by industry and pooled data across various industries, results might be misleading. Strong results in one industry could be offset by weak results in another industry, thus showing weak statistical significance when pooled across industries.

Cash Flow Theory

The belief that the usefulness of cash flows is industry specific is consistent with cash flow theory. Cash flow theory can be traced to the concept of financial flexibility advocated by Heath (1978). According to Heath (p. 20), financial flexibility is the capacity of a firm "to control cash receipts and payments to survive a period of financial adversity." The ultimate aim of financial flexibility is to achieve a state of equilibrium in total cash flow so that the available purchasing power will be equal to the needs set by established limits and management decisions. The concept of financial flexibility indicates that the occurrence of certain events triggers an unexpected drop in total cash flow, thus forcing a company to take corrective action to regain cash flow equilibrium. The activities taken by management in restoring cash flow equilibrium dictates the future cash flows. Some events occur suddenly, while others can be cyclical in nature. Examples of events are: decline in sales, slowdown in accounts receivable, price or wage increases (contract negotiations), change in general economic condition (recession), increased competition (innovation), and management behavior.

Management has many strategies for corrective action to regain cash flow equilibrium to avoid financial distress. According to Heath, some of these strategies to avoid financial distress include: (1) borrowing money, either directly by borrowing from banks, selling bonds, etc., or indirectly by delaying payments to creditors, and allowing accounts payable to build, etc.; (2) liquidating assets either directly by selling assets, or indirectly by failing to replace inventory as the inventory is sold or failing to replace fixed assets consumed in operations, etc.; (3) reducing costs; (4) reducing dividends; and (5) issuing capital stock (p. 21). The success of management's attempts to regain cash flow equilibrium dictates whether a firm recovers or progresses toward eventual financial distress.

The events causing the initial decrease in total cash flow are often industry specific. The options available to management to regain cash flow equilibrium in times of decreasing cash flow would also differ by industry since these options depend on the financial structure of an organization.

For example, cash flow from investing activities should be very useful in predicting financially distressed mining, oil and gas firms because these firms require huge investments in long-term fixed assets. Mining, oil and gas firms investing in long-term assets would tend to be companies maintaining cash flow equilibrium, and these companies would have greater financial flexibility to recover cash flow equilibrium during sudden decreases in cash flow. Mining, oil and gas firms not investing in long-term assets, or those selling off their assets to regain cash flow equilibrium, are more likely to become financially distressed in the future.[2]

The purpose of this study is to determine if cash flow information is more useful to creditors in predicting financially distressed mining, oil and gas firms than it is in predicting financial distressed firms in other industries. This study uses two samples to address the objective, a sample of healthy and financially distressed mining, oil and gas firms and a sample of healthy and financially distressed firms not involved in natural resource recovery. Similar to previous studies, the control sample firms are matched by industry to eliminate industry effects.

The remainder of this paper is organized in three sections. The next section discusses the methodology and the sampling process used in this study. The second section presents the analysis and empirical results. The final section contains concluding remarks.

Research Methodology

Dependent and Independent Variables

The measure of financial distress used in this study was a binary distressed versus nondistressed measure. A firm was financially distressed if it: experienced a greater than forty percent reduction in cash dividend per share after a history of successive cash dividends per share, experienced a loan principal/interest default or debt accommodation, or filed for Chapter XI protection during 1988 or 1989.[3] Although bankruptcy is the most common measure used in financial distress research, a distressed versus nondistressed measure has been used in previous studies by Beaver (1966), Deakin (1972), Blum (1974), and Gilbert et al. (1990). A distressed versus nondistressed measure is also consistent with events research by Giroux and Wiggins (1984) and DeAngelo and DeAngelo (1990). The financial distress measure is the dependent variable in this study and is coded as follows:

DIST = 0	if firm was healthy (no event of financial distress) during 1988 or 1989, and
1	if firm was financially distressed during 1988 or 1989.

The independent variables examined consist of four control variables and three cash flow variables. The four control variables are accrual ratios used by Ohlson (1980) and Casey and Bartczak (1984 and 1985). The control variables are as follows:

SIZE	=	log(total assets),
NITA	=	net income/total assets,
TLOE	=	total liabilities/owners' equity, and
CACL	=	current assets/current liabilities.

The cash flow variables tested, based on the three net cash flows required by the FASB, are as follows:

CFFO	=	cash flow from operating activities,
CFFI	=	cash flow from investing activities, and
CFFF	=	cash flow from financing activities.

The author computed the independent variables from Compustat Research, *Full, and Industrial/Primary/ Supplementary/Tertiary tapes* (*Compustat* tapes).[4] To prevent heteroscedasticity, this study scaled the cash flow variables by total liabilities.[5]

Logistic Regression Prediction Models

Financial data were used to predict the financial distress of 1988 and 1989 firms using two separate samples, a sample of mining, oil and gas firms (MOG sample) and a sample of firms in other industries not involved in natural resource recovery (control sample).

Models were lagged one, two, and three years before the event of financial distress.

The financial distress prediction models were constructed using binary logistic regression (LR), proportional odds variation.[6] This procedure fits a regression model based on a transformed logit. Suppose the response variable can take on the ordered values 0 and 1, with i predictor variables, and defining P_0 as the probability that a firm is in state 0 given the vector $\mathbf{X} = (X_1, X_2, \ldots, X_i)$ of independent variables, the logit can be estimated as follows:

$$L = \ln [P_0 / (1-P_0)] = a + b_1X_1 + b_2X_2 + \ldots + b_iX_i, \quad (1)$$

where a is an intercept parameter and the b_i coefficients represent the effect of the ith explanatory variable on a firm's probability of ending up in state 0 or 1.

With the response variable taking on the ordered values 0 and 1, the conditional probability that the jth observation has response 0 or 1 is given by:

$$P(DIST = 0|\mathbf{X}_j) = P_0 = \frac{\exp^{(L)}}{1 + \exp^{(L)}}, \quad (2)$$

$$P(DIST = 1|\mathbf{X}_j) = P_1 = 1 - P_0, \quad (3)$$

where DIST = financial distress with levels 0 and 1 and $\mathbf{X}_j$ is the known vector of predictor variables corresponding to the jth observation.

The predictive accuracy of each model was validated using a jackknife approximation technique employed by SAS (1990). This procedure reduces the bias resulting from predicting observations also used to generate the prediction models.

Sample Selection

The author selected the control sample firms using the following sampling scheme.[7] *Compustat* tapes were used to identify firms that, after three years of consistent annual cash dividends per share, reduced their annual cash dividends per share by more than forty percent from the previous year for 1988 and 1989. *Wall Street Journal Index* and *Compact Disc Disclosure* were used to identify firms that, during 1988 or 1989, defaulted on loan principal/interest payments, renegotiated loan terms that extended cash payment schedules or reduced interest rates or principal payments, or declared bankruptcy. Healthy firms for 1988 and 1989 were randomly selected from the *Compustat* tapes. Firms selected were in the same four-digit industry code as a financially distressed firm but not identified as financially distressed during 1988 and 1989. Firms not included in *Compustat* and firms with incomplete data were dropped from the sample. Finally, the author examined all sample firms' SEC 10-Ks and annual reports (healthy and distressed firms) to validate the occurrence of a financial distress event, the date of the event, and other important information. Firms were dropped from the sample if the author could not verify the event, or if the date of the event could not be determined. The author also dropped firms from the sample if management was under investigation for fraudulent activities related to the misstatement of financial statement information or if firms had unreliable data (e.g., firms with unaudited financial statements). The same process was used to obtain a sample of financially distressed and healthy mining, oil and gas (MOG) firms. The author identified the MOG firms by their four-digit industry code.

The control sample included 334 firms of which 245 were healthy and eighty-nine were financially distressed. The MOG sample included fifty-one firms of which thirty-seven were healthy and fourteen were financially distressed (forty-three firms are oil or gas and the other eight are mining firms).

Some firms issue their financial reports for the preceding year after the announcement of bankruptcy. Consequently, these financial reports include information about a firm's bankruptcy. This problem also can occur for firms experiencing a default or debt accommodation. Therefore, this study substitutes reports from the previous fiscal year for the most current year of interest for firms releasing their financial reports after the date of financial distress.

Analysis of Results

Prediction Models

Logistic regression is a robust statistical technique providing a sufficient sample size is used to generate the prediction models. Freeman (1987) and Stone and Rasp (1991) show that sample sizes of 10(S+1) or lower, where S is the number of predictor variables, can result in biased probit and logistic parameter estimates. However, small sample sizes in a single group (one group of a two group dependent variable such and healthy versus distressed) does not appear to cause parameter estimate bias.

Because the MOG sample size is less than 10(S+1) for the models in this study, bias is likely present in the parameter estimates generated by the MOG sample

Table 1
Incremental Predictive Power of Cash Flows: the Addition of Cash Flow Variable(s) to the Base Accrual Model SIZE + NITA + TLOE + CACL

		Control Sample			MOG Sample		
Model Year	Cash Flow[1] Variable(s) Added	Change in -2Log L[2]	Degrees of Freedom	P-Value	Change in -2Log L	Degrees of Freedom	P-Value
Year - 1:	CFFO	24.78	1	.000	6.25	1	.012
	CFFI	1.99	1	.158	6.19	1	.011
	CFFF	1.10	1	.294	.01	1	.920
	Best combination	27.80	2	.000	9.44	2	.008
Year - 2:	CFFO	16.07	1	.000	3.68	1	.055
	CFFI	.99	1	.319	5.31	1	.021
	CFFF	6.69	1	.009	2.86	1	.090
	Best combination	16.69	2	.000	8.42	2	.014
Year - 3:	CFFO	3.11	1	.077	1.78	1	.182
	CFFI	2.12	1	.145	1.45	1	.228
	CFFF	.98	1	.322	.01	1	.920
	Best combination	5.27	2	.071	3.58	2	.166

[1] Each cash flow was added separately to the base accrual model SIZE + NITA + TLOE + CACL; then, all possible combinations of the cash flows were added to the base accrual model (CFFO+CFFI, CFFO+CFFF, CFFI+CFFF, and CFFO+CFFI+CFFF). The best combined model is also reported for each sample. For the control sample, the CFFO+CFFF model was the best combined model for all three years. For the MOG sample, the CFFO+CFFI was the best combined model for all three years.

[2] Change in -2Log Likelihood - the change in the -2Log Likelihood statistics for the base accrual and cash flow(s) added models (distributed as a chi-square distribution). A significant Change in -2Log Likelihood chi-square indicates that the added cash flow variable(s) has(ve) incremental explanatory power over traditional accrual net ratios.

models. In situations where parameter estimates are biased (either from collinearity or small sample sizes), the Wald χ^2 statistic for each parameter estimate is not the best measure of an added variable's predictive power. Instead, the preferred measure is the change in the overall model's log likelihood statistic when adding a variable. Thus, this study uses the Change in -2Log Likelihood for the added cash flow variable as the test statistic for each cash flow variable.[8]

To ascertain the incremental explanatory power of cash flows, this study adds each cash flow variable separately to a base accrual model incorporating the four accrual variables. Then, all combinations of the cash flow variables are added to the accrual model. Table 1 includes the results for the models with each cash flow variable added separately and the best combined cash flow model, lagged one, two, and three years before financial distress.

The results show that the strongest cash flow variable for the control sample is CFFO, which is significant one and two years before financial distress (at p-value < .05). This result is consistent with prior studies, although stronger with the mining, oil and gas firms not in the sample. (Normally, prior studies found that operating cash flow is only incrementally significant one year before financial distress.) CFFF also has significant incremental predictive power in year - 2. However, CFFI never provides significant explanatory power for the control firms.

The biggest difference in the results for the two samples is that CFFI is a strong incremental predictive cash flow variable for the mining, oil and gas firms. Although CFFO is also an important predictor variable for the mining, oil and gas firms one and two years before financial distress, CFFO is not as powerful as it is for the control sample. The combined model with both CFFO and CFFI included shows the strongest incremental predictive significance of any cash flow model for the MOG sample in years one and two.[9]

The parameter estimates for CFFO, CFFI, and CFFF are reported in Table 2. The parameter estimates for CFFO show that, for both samples, financially distressed firms are significantly more likely to have lower (or negative) cash flow from operating activities one and two years before financial distress than healthy firms. The parameter estimates for CFFI show that financially distressed mining, oil and gas firms are significantly more likely to have cash inflows (or lower outflows) from investing activities than healthy firms one and two years before financial distress.

The classification results even better illustrate the disparities in the importance of cash flows for the two samples. Classification results show that, for the control firms, adding the cash flows to an accrual only model improves predictions very little. Even the CFFO model fails to improve the classification rates substantially. This result is consistent with prior cash flow research.

However, the results show that cash flows do improve classification rates for the mining, oil and gas firms when added to the accrual model. CFFI improves classification rates all three years, while the combined CFFO and CFFI model is very strong one and two years before financial distress. The addition of CFFI (CFFO and CFFI in year - 2) improves the model's prediction accuracy for the mining, oil and gas firms much more than for the control firms. The results show that the cash flows, especially CFFI, are useful in improving the predictions of financially distressed mining, oil and gas firms (accuracy rate improves from 50% to 71.4% when CFFI is added to the accrual variables in year - 1).[10]

Table 2
Parameter Estimates for the Cash Flow Variables after Adding Each One to the Base Accrual Model SIZE + NITA + TLOE + CACL

Model Year	Cash Flow[1] Variable	Control Sample Parameter Estimate	MOG Sample Parameter Estimate
Year - 1:	CFFO	-4.1403	-3.4922
	CFFI	1.1293	2.5032
	CFFF	0.5670	0.0650
Year - 2:	CFFO	-1.8378	-2.4449
	CFFI	.5796	3.7638
	CFFF	1.1432	-1.7514
Year - 3:	CFFO	-0.5016	-1.0742
	CFFI	0.4566	0.8053
	CFFF	-0.1796	-0.0134

[1] Each cash flow was added separately to the base accrual model SIZE + NITA + TLOE + CACL.

Classification Accuracy (Jack-Knife Technique) of Prediction Models

The results of the statistical models were validated by determining the ability of each model to classify correctly firms in each sample. Table 3 shows the classification results for the base accrual and cash flows (combined) models.

Comparisons With Naive Models

A prediction model must out-predict a naive chance model to be considered practically useful to creditors. However, selection of a naive model is very subjective. For example, researchers often use a fifty percent

Table 3
Validation of Statistical Models Using Classification Accuracy

		Percentage Classified Correctly					
		Control Sample[1]			MOG Sample		
Year	Model[2]	Total[3]	Healthy	Distressed	Total	Healthy	Distressed
Year - 1:	Base Accrual	79.3	94.3	38.2	84.3	97.3	50.0
	CFFO added	81.1	92.7	49.4	84.3	91.9	64.3
	CFFI added	79.0	94.3	37.1	88.2	94.6	71.4
	CFFF added	79.3	94.3	38.2	80.4	91.9	50.0
	Best combination	81.4	93.5	48.3	88.2	91.9	78.6
Year - 2:	Base Accrual	78.2	96.7	27.0	76.5	88.9	42.9
	CFFO added	78.8	95.5	32.6	82.0	91.7	57.1
	CFFI added	78.8	97.2	28.1	82.0	91.7	57.1
	CFFF added	76.4	94.3	27.0	80.0	91.7	50.0
	Best combination	78.2	94.7	32.6	86.0	91.7	71.4
Year - 3:	Base Accrual	74.3	96.7	12.4	68.6	91.9	7.1
	CFFO added	73.4	95.5	12.4	66.7	89.2	7.1
	CFFI added	74.0	96.3	12.4	70.6	91.9	14.3
	CFFF added	74.0	96.7	11.2	68.6	91.9	7.1
	Best combination	73.1	95.1	12.4	68.6	89.2	14.3
Each year:	Naive model	73.3			72.5		

1 The control sample included 334 firms of which 238 were healthy and 96 were financially distressed. The MOG sample included 51 firms of which 37 were healthy and 14 were financially distressed.

2 Each cash flow was added separately to the base accrual model SIZE + NITA + TLOE + CACL; then, all possible combinations of the cash flows were added to the base accrual model (CFFO+CFFI, CFFO+CFFF, CFFI+CFFF, and CFFO+CFFI+CFFF). The best combined model is also reported for each sample. For the control sample, the CFFO+CFFF model was the best combined model for all three years. For the MOG sample, the CFFO+CFFI was the best combined model for all three years.

3 The classification rates represent the total percentage of firms correctly classified, the percentage of healthy firms correctly classified, and the percentage of distressed firms correctly classified by the relevant model for each sample.

probability for a chance model. However, this naive benchmark is a weak test of a model's classification ability when the proportion of healthy firms greatly exceeds the proportion of distressed firms. All models in this study, for both MOG and control samples, have classification rates exceeding fifty percent.

A better benchmark is to assume that a naive model would classify all observations as healthy firms. Thus, this naive model would correctly classify 73.35% (245/334) of the control firms and 72.55% (37/51) of the mining, oil and gas firms. A comparison of the models' classification rates with this naive model shows that all models out-predict the naive model one and two years before financial distress for the MOG sample, while most models out-predict the naive model all three years for the control sample.

Choice-Base Sampling Bias

Since dichotomous financial distress studies use nonrandom techniques to select bankrupt and non-bankrupt firms, previous researchers argued that binary probit and logistic bankruptcy models generate biased parameter estimates (e.g., Zmijewski, 1984). However, according to Maddala (1991), one does not need to use a weighing procedure for the logit model because the unequal sampling rates do not affect the logit coefficients of the predictor variables; only the constant term is affected. The constant term simply needs to be decreased by log p_1 - log p_2, the proportions sampled from each group (population) to control for the bias. Thus, test statistics are not affected by this bias, nor are comparisons across models. Adjusting the intercept would simply result in the correct classification of more healthy firms and the correct classification of fewer distressed firms for each model, with a resulting increase in total classification rates. Results from comparisons between the two samples' classification rates should be the same.

Further Validation of Results

The author attempted to determine whether sample differences could be confounding the results. For example, the results could be affected by the fact that the MOG sample includes both mining and oil and gas firms, or by the fact that some mining, oil and gas firms were not primarily involved in natural resource exploration and recovery during the estimation period. To determine the effect of these two items on results, the author reran all models for the MOG sample with only the oil and gas firms included (sample size of forty-three firms) and reran all models for those mining, oil and gas firms identified by SEC 10-Ks as primarily exploration and recovery firms (sample size of 45 firms). The results were almost identical with the results reported earlier for the full MOG sample.

The MOG sample in this study contains a smaller percentage of least distressed firms than the control sample does (seven percent of the distressed firms in the MOG sample were dividend default firms, while thirty-one percent of the distressed firms in the control sample were dividend default firms). This difference in severity of distress between the two samples could have affected the results showing a difference in the importance of cash flows for the control and MOG samples. Thus, the author dropped the dividend reduction/default firms from the samples and replicated the study. The results were the same as reported earlier for the full samples.

Conclusions

Many firms spend substantial time and cost maintaining the records to prepare a statement of cash flows. Yet, prior dichotomous financial distress research studies have found little evidence that the three net cash flows required on a statement of cash flows have usefulness in predicting financial distress, except possibly cash flow from operating activities (CFFO). However, these studies failed to determine whether cash flow information may be more useful to a particular industry.

This study used two separate samples to determine whether or not cash flow information is more useful to creditors for predicting financially distressed mining, oil and gas firms. Results do show that cash flow information may be more useful to creditors for predicting financially distressed mining, oil and gas firms than for other industries, especially cash flow from investing activities (CFFI). CFFI is the most important predictor of financial distress for mining, oil and gas firms, while CFFO is the most important predictor of financially distressed firms in industries not involved in natural resource recovery.

None of the cash flows improved classification rates substantially for the control sample when added to accrual ratios. However, CFFI did improve classification rates of mining, oil and gas firms when added to accrual ratios, resulting in substantial increases in the correct classification of financially distressed mining, oil and gas firms all three years before the financial distress event. Apparently, financially distressed mining, oil and gas firms are more likely to have cash inflows (or lower cash outflows) from investing activities one and two years before financial distress than healthy firms.

The above results illustrate the importance of determining whether the predictive usefulness of accounting information may be industry specific. Methods useful in one industry may not be useful in other industries. Prior financial distress research has ignored this possibility. This study's results for the control sample are similar to results found in prior studies. However, when mining, oil and gas firms are considered by themselves, results differ.

Suggestions for Future Research

This study's results suggest that researchers must take care in generalizing results of financial distress models from data pooled across different industries. Future research should attempt to determine whether or not cash flow information is useful in other asset intensive industries such as manufacturing. Also, since financial distress research has been used to test the usefulness of various accounting information over the last twenty-five years (e.g., constant dollar/current value accounting), future research should address whether this prior research is valid across all industries. Future financial distress researchers should also attempt to determine if their reported results are affected by the way they pool their sample firms' data.

Footnotes

1. Ward (1992, pp. 31-37) did find that the gross cash flows that make up net cash flow financing activities may have predictive usefulness. However, Ward used a four-state measure of financial distress (healthy, dividend reduction, loan default, and bankrupt) instead of a dichotomous measure (healthy versus distress or nonbankrupt versus bankrupt) as used in prior studies. Thus, comparisons of Ward's study with previous financial distress studies is somewhat difficult.
2. Cappel (1990, pp. 79-80) provides a good discussion of the expected usefulness of cash flow information to investors for oil and gas firms. Much of his discussion is also relevant for creditors.
3. Choosing a criterion for selecting the dividend reduction firms is arbitrary. The author chose a forty percent criterion because a forty percent dividend reduction after a history of successive payments (three years) should be large enough to affect the stockholders adversely.
4. Cash Flow from Operating Activities (CFFO) = Income before extraordinary items + depreciation and amortization + deferred tax expense and investment tax credit + equity in net loss (earnings) + loss (gain) from sale of property, plant, and equipment and investments + funds from operations-others + accounts receivable-decrease (increase) + inventory-decrease (increase) + other current assets-decrease (increase) + current liabilities other than current debt-increase (decrease). Cash Flow from Investing Activities (CFFI) = sale of property, plant and equipment - capital expenditures - acquisitions - increase in investments + sale of investments + short-term investments-change (if reported separately). Cash Flow from Financing Activities (CFFF) = change in long-term debt + change in current debt + sale of common and preferred stock - purchase of common and preferred stock - cash dividends.
5. The author also ran the models with the cash flows scaled by total assets, current assets, current liabilities, and sales. This study reports the results for the models with cash flows scaled by total liabilities because scaling by total liabilities produced consistently strong results for both samples, control and mining, oil and gas samples. The author also ran the models with CFFO scaled by current assets, CFFI scaled by sales, and CFFF scaled by owners' equity. Ward (1993) found in an earlier dichotomous financial distress study that scaling the relevant cash flows by these different measures produced the strongest prediction results. Using the different scaling measures did produce the strongest prediction results for the control sample's firms in this study. However, they produced weak prediction results for the mining, oil, and gas sample's firms. All scaling measures used still produced the same conclusions concerning comparisons of results between the two samples.
6. The author used the Proc Logistic command in SAS (1990) to generate the logistic statistical models. Hosmer and Lemeshow (1989) provide a thorough discussion of binary logit regression.
7. Firms in finance, banking, and utility industries were excluded from the control sample.
8. Hosmer and Lemeshow (pp. 11-18 and pp. 223-226) provide a good discussion of techniques used in logistic regression to evaluate the significance of independent variables.
9. The use of the Change in -2Log Chi-square and classification accuracy should result in reliable conclusions concerning the usefulness of cash flow information. However, any bias in this study resulting from the small sample size should be biased against finding significance of cash flow information for the mining, oil and gas firms (Stone and Rasp, 1991). Thus, results showing that cash flows are useful are still valid. In reality, results should be stronger than shown in this study.
10. Researchers often use statistical tests such as a Z-test of proportions (e.g., Morris and Nichols, 1988) to determine whether the differences between models' classification rates are practically important. However, according to Kennedy (1992), "test results depend upon the size of the differences, variability of the accuracy, and sample sizes" (p. 434). These tests of differences in proportions can lead to misleading conclusions when comparing results from different samples, especially when one sample is much larger than the other sample, as in this study. Thus, the author of this study did not test significances of the differences between the models' classification rates. Instead, the author used the classification rates to validate the statistical results reported in Table 1.

References

1. Aziz, A., D. C. Emanuel and G. H. Lawson, "Bankruptcy Prediction - An Investigation of Cash Flow Based Models," *Journal of Management Studies,* Vol. 25, pp. 419-437, 1988.
2. ____ and G. H. Lawson, "Cash Flow Reporting and Financial Distress Models: Testing of Hypotheses," *Financial Management,* Vol. 18, pp. 55-63, 1989.
3. Beaver, W. H., "Financial Ratios as Predictors of Failure," *Journal of Accounting Research,* Vol. 4, pp. 71-127, 1966.
4. Blum, M., "Failing Company Discriminant Analysis," *Journal of Accounting Research,* Vol. 12, pp. 1-25, 1974.
5. Cappel, J. J., "Divergent Treatment in Calculating

Operating Cash Flows," *Petroleum Accounting and Financial Management,* Spring, pp. 74-106, 1990.
6. Casey, C. J. and N. J. Bartczak, "Cash Flow-It's Not the Bottom Line," *Harvard Business Review,* Vol. 62, pp. 61-66, 1984.
7. ______ and __________, "Using Operating Cash Flow Data to Predict Financial Distress: Some Extensions," *Journal of Accounting Research,* Vol. 23, pp. 384-401, 1985.
8. Deakin, E., "A Discriminant Analysis of Predictors of Business Failure," *Journal of Accounting Research,* Vol. 10, pp. 167-179, 1972.
9. DeAngelo, H. and L. DeAngelo, "Dividend Policy and Financial Distress: An Empirical Investigation of NYSE Firms," *The Journal of Finance,* Vol. 95, pp. 1415-1431, 1990.
10. Freeman, D. H., *Applied Categorical Data Analysis,* Marcel Dekker, Inc., New York, NY, 1987.
11. Gentry, J. A., P. Newbold and D. T. Whitford, "Classifying Bankrupt Firms with Funds Flow Components," *Journal of Accounting Research,* Vol. 23, pp. 146-160, 1985.
12. ________ , ______ and ________, "Funds Flow Components, Financial Ratios, and Bankruptcy," *Journal of Business Finance and Accounting,* Vol. 14, pp. 595-606, 1987.
13. Gilbert, L. R., K. Menon and K. B. Schwartz, "Predicting Bankruptcy for Firms in Financial Distress," *Journal of Business Finance and Accounting,* Vol. 17, pp. 161-171, 1990.
14. Giroux, G. A. and C. E. Wiggins, "An Events Approach to Corporate Bankruptcy," *Journal of Bank Research,* Vol. 15, pp. 179-187, 1984.
15. Heath, L. C., *Financial Reporting and the Evaluation of Solvency,* AICPA, New York, NY, 1978.
16. Hosmer, D. W. and S. Lemeshow, *Applied Logistic Regression,* John Wiley, New York, NY, 1989.
17. Kennedy, D. B., "Classification Techniques in Accounting Research: Empirical Evidence of Comparative Performance," *Contemporary Accounting Research,* Vol. 8, pp. 419-442, 1992.
18. Maddala, G. S., "A Perspective on the Use of Limited-Dependent and Qualitative Variables Models in Accounting Research," *The Accounting Review,* Vol. 66, pp. 788-807, 1991.
19. Morris, M. H. and W. D. Nichols, "Consistency Exceptions: Materiality Judgments and Audit Firm Structure," *The Accounting Review,* April, pp. 237-254, 1988.
20. Ohlson, J. A., "Financial Ratios and the Probabilistic Prediction of Bankruptcy," *Journal of Accounting Research,* Vol. 19, pp. 109-131, 1980.
21. SAS Institute Inc., *SAS/STAT User's Guide, Version 6,* Fourth Edition, Vol. 2, SAS, Cary, NC, 1990.
22. Stone, M. and J. Rasp, "Tradeoffs in the Choice Between Logit and OLS for Accounting Choice Studies," *The Accounting Review,* Vol. 66, pp. 170-187, 1991.
23. Ward, T., "The Incremental Predictive Ability of Net and Gross Cash Flows Using Four-State Ordinal Models of Financial Distress," *The Southern Business and Economic Journal,* Vol.16, pp. 26-44, 1992.
24. , "Is the Scaling Measure Used for Cash Flows Important in Predicting Financially Distressed Firms?," *Journal of Applied Business Research,* Vol. 9, pp. 134-140.
25. Zmijewski, M. E., "Methodological Issues Related to the Estimation of Financial Distress Prediction Models," *Journal of Accounting Research,* Vol. 22, pp. 59-82, 1984.