Predicting Corporate Financial Distress: Reflections on Choice-Based Sample Bias

*Harlan D. Platt and Marjorie B. Platt**

Abstract

Financial distress precedes bankruptcy. Most financial distress models actually rely on bankruptcy data, which is easier to obtain. We obtained a dataset of financially distressed but not yet bankrupt companies supplying a major auto manufacturer. An early warning model successfully discriminated between these distressed companies and a second group of similar but healthy companies. Previous researchers argue the matched-sample design, on which some earlier models were built, causes bias. To test for bias, the dataset was partitioned into smaller samples that approach equal groupings. We statistically confirm the presence of a bias and describe its impact on estimated classification rates. (*JEL* G30 or G33)

Introduction

Assessing the financial strength of companies has traditionally been the domain of parties external to the firm, such as investors, creditors, auditors, government regulators, and other stakeholders. More recently, because competition has spawned intimate relationships between manufacturers and their component suppliers, now manufacturers are concerned about the financial health of their suppliers and vice versa. From a supply chain management perspective, if a manufacturer can help one of its suppliers ameliorate problems and thereby avoid bankruptcy, it is in both parties' interest to do so. Reliance on reactive distress signals such as delayed shipments, problems with product quality, warnings from the supplier's bank, or observations made during company visits to indicate near-term financial difficulties reduces the options and the time available to act and remedy the situation.

An early warning system model that anticipates financial distress of supplier firms provides management of purchasing companies with a powerful tool to help identify and, it is hoped, rectify problems before they reach a crisis. Because of long-term contracts with selected and certified suppliers, large manufacturers are increasingly interested in the financial health of these suppliers in order to avoid disruption to their own production and distribution schedules. Financial distress is defined as a late stage of corporate decline that precedes more cataclysmic events such as

* Harlan D. Platt, College of Business Administration, Northeastern University, h.platt@neu.edu; Marjorie B. Platt, Harold A. Mock Professor of Accounting, College of Business Administration, Northeastern University.

bankruptcy or liquidation. Information that a firm is approaching distress can precipitate managerial actions to forestall problems before they occur, can invite a merger or takeover by a more solvent or better-managed enterprise, and can provide an early warning of possible future bankruptcy.

While there is abundant literature describing prediction models of corporate bankruptcy, few research efforts have sought to predict corporate financial distress. The lack of work on financial distress results in part from difficulty in defining objectively the onset of financial distress. By contrast, the bankruptcy date is definitive and financial data prior to that date are reasonably accessible. As a consequence of the indeterminacy of when a firm becomes financially distressed, most research that purports to study financial distress instead examines the terminal date associated with the company's filing for bankruptcy protection. Our work examines financial distress in just a single industry, auto suppliers, because of a unique opportunity we had to work with the largest consulting firm working with that industry.

Regardless of the specific focus of an early warning system model, bankruptcy or financial distress, the sample design employed to build the model may result in biased estimated coefficients causing inaccurate predictions, at best. The sample design employed by many research studies has been to match a set of bankrupt firms with the same number or some multiple of healthy firms, often controlling for size or industry. For example, in his seminal study, Altman (1968) matched 33 failed companies with 33 healthy firms. Zmijewski (1984) argued persuasively that matching with anything less than the entire population of healthy firms when using logit regression or MDA would result in biased coefficients and unreliable predictions. Yet, many subsequent studies (Altman et al. 1994; Gambola et al. 1987; Lin et al. 1999; Platt and Platt 1991a; Theodossiou 1993; Theodossiou et al. 1996) continued to rely on matched samples or partially adjusted unequal matched samples to test alternative methodologies or estimation methods.

This study builds a logit model to predict financial distress among companies in the automobile supplier industry (SIC 3714 or NAICS 3363). Financial distress, rather than bankruptcy status, was the categorical dependent variable in the model. All publicly traded firms in the COMPUSTAT database, as recommended by Zmijewski (1984), as well as all financially distressed firms supplying one large Detroit-based automobile manufacturer were used to build the model. Simulations were then run to test the theoretical claim of bias advanced by Manski and Lerman (1977) and Palepu (1986) and weakly tested empirically by Zmijewski (1984). A full range of statistical tests indicate that, with a full population, a reliable predictive model of financial distress correctly bifurcates 98 percent of all firms into those likely to experience financial distress in the subsequent year and those likely to remain healthy. Moreover, simulations showed that bias increased substantially when the sample design departed in steps from the original population of all firms in the automobile supplier industry, as expected.

Literature Review

Prediction of bankruptcy occupies a long and accomplished history. Efforts to differentiate between failed and non-failed firms began with Beaver's (1966) early use of individual ratios, moved to the Altman's (1968) Z-score based on multiple discriminant analysis, and has currently witnessed recent innovations, most notably the use of industry-relative data (Platt & Platt 1991a); and neural networks (Altman, Marco, and Varetto 1994; Yang, Platt, and Platt 1999). These models have proved beneficial in a variety of applications, including portfolio selection (Platt and Platt 1991b), credit evaluation (Altman and Haldeman 1995; Platt and Platt 1992), and turnaround management (Platt and Platt 2000). Users of these models include creditors concerned with defaults, suppliers focused on repayment, and potential investors.

Studies of corporate distress have mostly focused on the issue of financial restructurings (Gilson, John, and Lang 1990; Wruck 1990; Brown, James, and Mooradian 1992) and management turnover (Gilson 1989). There have been limited attempts to produce models that predict financial distress (Schipper 1977; Lau 1987; Hill et al. 1996). Further, many studies that purportedly focus on financial distress, based on their title, in fact model bankruptcy status, based on their operational definition of financial distress (Frydman, Altman, and Kao 1985; Theodossiou, Kahya, and Philippatos 1996; Lin, Ko, and Blocher 1999). A roadblock limiting efforts to predict financial distress has been the lack of a consistent definition of when companies enter that stage of decline. Samples of firms that might be considered to be in distress have been created by examination of various markers: Lau (1987) and Hill et al. (1996) use layoffs, restructurings, or missed dividend payments; Asquith, Gertner, and Scharfstein (1994) allow an interest coverage ratio to define distress; similarly, Whitaker (1999) measures distress as the first year in which cash flow is less than current maturities of long-term debt; and John, Lang, and Netter (1992) let the change in equity price define distress. The problem with these indicators is that some companies engaging in those activities are not actually in distress. Layoffs may occur in specific divisions of otherwise healthy enterprises, restructurings may occur at different stages of decline, and there are many explanations for missed dividend payments. Perhaps these definitional difficulties contribute to the lack of success of prior empirical efforts regarding financial distress.

Another group of researchers, notably Donald Bibeault (1998) and Charles Hofer (1980), describe financial distress from a turnaround management perspective. Bibeault describes stages that depict companies moving from financial distress to recovery; in contrast, Hofer tracks healthy firms succumbing to financial distress. The centerpiece of his analysis is the concept of break-even or operating income.

Like a variety of researchers, our work explores conditions within a single industry: auto suppliers. Guffey and Moore (1991) examined trucking; Platt, Platt, and Pedersen (1994) considered the oil and gas industry; Pantalone and Platt (1987) modeled failure of commercial banks; and Schipper (1977) predicted the financial condition of private colleges. Provided that a sufficiently large data set is obtained, single industry studies avoid issues arising in multi-industry studies such as differing accounting treatment of variables, cost, and capital structures as well as econometric concerns regarding data normality and stability over time.

Another problem with many early warning prediction models is choice-based sample bias (Zmijewski 1984), which results when models are built using data sets that contain only a fraction of the target population of companies. Because bankruptcy transactions are relatively rare events, Zmijewski argues that unless one builds a model based on the entire population, the estimated coefficients will be biased, and the resulting predictions will over-estimate the proportion of bankrupt firms that are correctly classified as such. The remedy is to use a sample that is as close to the population as possible.

While Zmijewski and others (Manski and Lerman 1977; Palepu 1986) clearly articulate the choice-based sample bias problem, Zmijewski's empirical test was weak. He compares results from the entire population of firms to those generated from several samples that were matched using varying numbers of healthy firms. For each sample size, Zmijewski reports the results of one regression and calculates the correlation coefficients between the percentage of bankrupt firms in the sample and the various estimated coefficients as well as the constant term. He finds significant correlations between the percentage of bankrupt firms in the sample and the estimated coefficient that are consistent with bias. Because he ran only one regression for each sample size, he could not test the individual estimated coefficients for bias against the population parameter, a more direct test of bias. By contrast, we use more standard tests of bias, comparing the mean estimated coefficient to the population parameter.

Methodology

Population of Automotive Supply Companies

With the assistance of a large turnaround-consulting firm, BBK Ltd.,[1] that specializes in a single industry (automotive suppliers), a list of public and private firms was compiled that had required the consultant's services to recover from distress. The firm provides all of the turnaround consulting work required by external suppliers of one of the big three automotive firms. BBK Ltd. provided us with access to 25 distressed companies: 21 private and four public firms. Of these, 21 had sufficient data to complete the needed data items for the analysis, including 18 financially distressed private and three financially distressed public firms. With the companies all in the same industry, there was no need to use the Platt and Platt (1991a) industry-relative normalization.

The list of companies provided by BBK Ltd. was augmented by a review of financial databases and publicly available news reports or press releases to locate additional public automotive supply companies, not working with the consultants, that had reported markers identified by others as indicating financial distress. Hofer's (1980) attention to operating income as a critical factor in cases of financial distress was a primary focus, though the search included other gauges as well. Therefore, we searched for companies reporting one or several of the following indicators:

- several years of negative net operating income (similar to Hofer 1980; Whitaker 1999);
- suspension of dividend payments (similar to Lau 1987);
- major restructuring or layoffs (similar to Hill 1996).

We asked the consultants who intimately knew the industry to confirm that the financial distress cases obtained from the search were real; they spoke, in addition, with bankers and company executives. BBK Ltd. is the largest turnaround firm in the automotive supply industry. It was able to indicate which of the additional firms that we identified had actually progressed to a stage of decline similar to that experienced by their client companies included in our database. With the secondary effort the total number of distressed firms in the population rose to 24 (21 private and three public). The total universe of auto suppliers is the appropriate group to compare against these distressed companies. We obtained data on 62 non-distressed companies including all 58 public non-distressed auto supply companies in the COMPUSTAT database and four private firms whose data came from BBK Ltd.

Operational Definition of Financial Distress

For analysis purposes, the dependent variable was defined as the actual status of the automotive supplier firm: financially distressed or healthy. BBK Ltd. performs all the workout assignments for a major automobile company. While the manufacturer prefers to allow its suppliers to operate independently, the company depends on these suppliers for its inputs (often with sole source contracts); thus, it would prefer that interventions occur in the mid-stage of financial distress at the latest, but lacking an early warning model to provide warnings, some suppliers have filed for bankruptcy before the manufacturer was aware of their condition. Overall, we characterize the stage of distress of the companies in our data set as being serious but not fatal. While this description is inexact, it includes companies whose troubles exceed the early stage symptoms of negative earnings before interest and taxes (EBIT), net income, or cash flow. These are companies that have had trouble paying their own suppliers, have missed payments to their bank, or may have difficulty making the next payroll. Further, most have sustained net losses for

[1] We especially appreciate the efforts of Peter Pappas of BBK Ltd. on our behalf.

several years or have suspended dividend payments in an effort to marshal financial resources to deal with operational or debt-related problems. Without any intervention it is likely that most, if not all, of these firms would eventually file for bankruptcy protection.[2] Our modeling effort aims to create a tool that provides an early gauge of when an auto supplier will need turnaround guidance. Financially distressed firms were arbitrarily assigned a value of 1, while the healthy firms were assigned a value of 0.

Financial distress occurs before bankruptcy as depicted in Figure 1. Panel A illustrates that the identification of the onset of financial distress using any of the measures described above occurs prior to the hypothetical date on which a firm would file for bankruptcy. We speculate that the onset of financial distress might predate the likely bankruptcy date by as much as three years. The prediction of bankruptcy more than three years out is difficult. Altman's (1968) widely acclaimed model is only 29 percent accurate using data four years prior to bankruptcy, 48 percent accurate three years prior to bankruptcy, and 72 percent accurate two years before bankruptcy. Financial distress is more difficult to predict than bankruptcy because of indeterminacy about its start date. The upward sloped line in the first panel indicates that a company is less likely to be identified as financially distressed the further removed it is from the hypothetical bankruptcy date.

Panels B and C in Figure 1 illustrate the relationship between the onset of financial distress and the date at which financial data are gathered for this study. Panel B shows that, on average, our data precede the date of financial distress, which coincides with the hypothetical bankruptcy date by 13.5 months. Panel C shows that, at the earliest, the data are 49.5 months prior to the time of the likely bankruptcy.[3] It is assumed that most companies are in reasonably good shape a year prior to the onset of financial distress. Therefore, it is difficult for even an astute observer to forecast likely future financial distress without the aid of a statistical model that provides systematic, objective analysis.

The onset of distress was assumed to be coincident with the date BBK Ltd. was hired to manage the distressed company or concurrent with the public announcement of a "distress-like event" for distressed companies not working with BBK Ltd., provided that the consultants judged the case as equal in severity to those they handled. For data-gathering purposes we had to match the date of distress for healthy firms and distressed firms because firms varied in the date of their financial distress. In selecting which firms to match with respect to time, we relied on size of firm, measured by total assets. This procedure controls for the impact of varying macroeconomic environments by comparing companies during the same period. Table 1 indicates the time period during which population companies went into distress. During most of the observation period, the economy and especially the automotive sector were strong and vibrant. Consequently, the early warning model dealt mostly with internal factors leading firms into distress. At some later date, it might be necessary to add factors to the model that account for macroeconomic conditions along the lines of Mensah (1984) and Platt et al. (1994).

[2] As a result of the counseling and advice of the turnaround consultant, all of the firms survived without resorting to bankruptcy court protection.

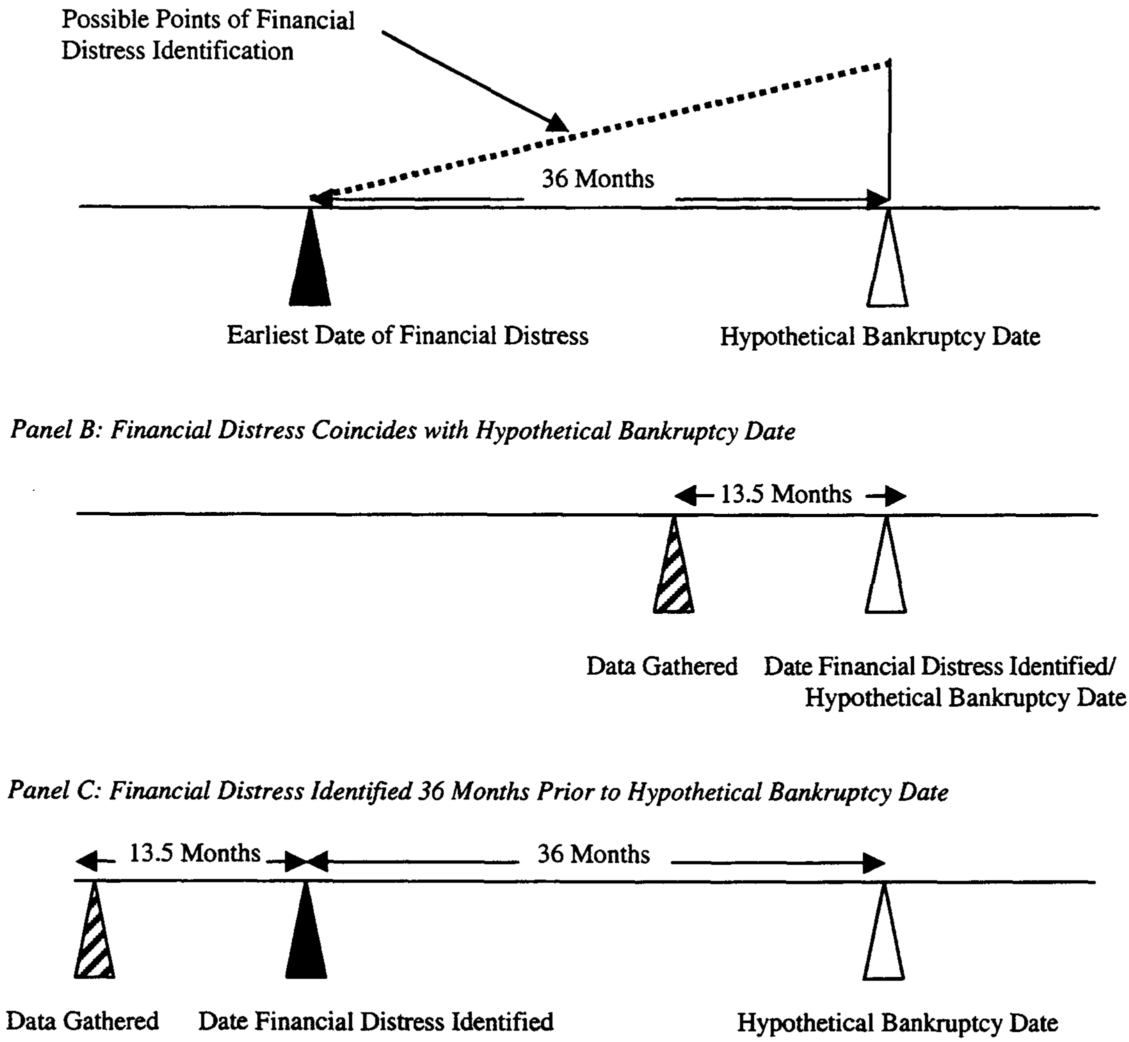
[3] A company was used for modeling purposes if there were financial data at least nine months prior to the date of financial distress. The number of months prior to financial distress ranged from nine to 18 months, with a mean of 13.5 months. This average lag between data observation and the target event date is consistent with common practice when constructing early warning system models (Altman 1968; Platt and Platt 1991a).

FIGURE 1. TIME LINE OF EVENTS FOR COMPANIES IN FINANCIAL DISTRESS

Panel A. Relationship between Financial Distress and Hypothetical Bankruptcy Date

Panel B: Financial Distress Coincides with Hypothetical Bankruptcy Date

Panel C: Financial Distress Identified 36 Months Prior to Hypothetical Bankruptcy Date



Independent Variables

Data from financial statements were obtained from COMPUSTAT for public firms and from financial statements obtained from BBK's files for private firms. In the latter case, these data tended to include unaudited figures. Unaudited values were carefully examined in consultation with BBK Ltd. Data were sought at least nine months before the onset of financial distress or for an equivalent time period for the healthy firms in the population; on average data preceded financial distress by 13.5 months.

TABLE 1. THE TIME PERIOD OF THE ONSET OF DISTRESS

Year that Distress Began	Number of Companies
1989	1
1990	2
1991	4
1992	1
1993	2
1994	3
1995	4
1996	3
1997	2
1998	2
Total	*24*

Individual financial items that were gathered are shown in Table 2 along with financial ratios that were created to measure profitability, liquidity, operational efficiency, leverage, and growth. As can be seen after reviewing Table 2, input data items were those typically reported on financial statements. Adjustments were made to estimate items sometimes not reported separately, such as depreciation and amortization. Notably, it was necessary to estimate the average proportion of the cost of goods sold that represented depreciation and amortization for all other firms in the industry. This figure was then used in the calculation of net cash flow for the privately held firms that did not report this figure separately.

Because a majority of companies in the population of firms available for analysis are classified as private, it is important to determine if private firms are fundamentally different from public firms or if the population distribution merely reflects the nature of BBK, Ltd.'s consulting engagements. Mean and median values for financial statement items for private and public companies are contained in Table 3. In addition, the p-values of t-tests comparing mean values and of χ^2 tests for difference between medians (Dixon and Massey, 1969) for the raw financial statement items are presented. Several observations can be made from examining Table 3. First, the distribution of both private and public firms are skewed positively, with means higher than medians. Second, given the lack of symmetry in the distribution, the median values are probably more representative of the central tendency of the distributions than the mean values. Thus, looking at the median values, it appears that public firms are significantly larger than private firms, based on total assets or net sales. Given that the two types of firms differ in size, we corrected for size differences by creating financial ratios, a standard approach used when building early warning system models (Altman, 1968).

TABLE 2. DATA AND FINANCIAL RATIOS EMPLOYED

Individual Financial Items		*Financial Ratios*		
Distress Date	Inventories (Inv)	*Profit Margin*	*Liquidity*	*Operating Efficiency*
Data Date	Inv (-1)	EBITDA/S	CA/CL	COGS/Inv
Status	Current Assets (CA)	NI/S	(CA-Inv)/CL	S/AR
Net Sales (S)	CA (-1)	CF/S	WC/TA	S/TA
S (-1)	Net Fixed Assets (NFA)	*Profitability*	CA/TA	AR/TA
COGS	NFA (-1)	EBITDA/TA	NFA/TA	S/WC
COGS (-1)	Total Assets (TA)	NI/TA	*Cash Position*	S/CA
Deprec+Amort (DA)	TA (-1)	EBIT/TA	Cash/CL	AR/Inv
DA (-1)	Accounts Payable (AP)	CF/TA	Cash/DA	(AR+Inv)/TA
SGA	AP (-1)	NI/EQ	Cash/TA	COGS/S
SGA (-1)	Notes Payable (NP)	*Financial Leverage*	*Growth*	SGA/S
EBIT	NP (-1)	TL/TA	S-Growth %	(COGS+SGA)/S
EBIT (-1)	Current Liabilities (CL)	CL/TA	NI/TA-Growth %	DA/S
Interest Expense (Int)	CL (-1)	CL/TL	CF-Growth %	DA/EBIT
Int (-1)	Long-term Debt (LTD)	NP/TA	*Miscellaneous*	S/CA
Net Income (NI)	LTD (-1)	NP/TL	EBIT/Int	
NI (-1)	Total Liabilities (TL)	LTD/TA	Int/S	
Cash	TL (-1)	EQ/TA	LTD/S	
Cash (-1)	Share Equity (EQ)	LTD/EQ	CF/Int	
Accounts Receivable (AR)	EQ (-1)		CF/TL	
AR (-1)			AP/S	

Calculated Items

EBITDA = EBIT + DA

EBITDA(-1) = EBIT (-1) + DA (-1)

CF = NI + DA

WC = CA - CL

Model Specification

The initial or core model specification utilized variables identified by Platt and Platt (1991a; 2000). Further model testing excluded insignificant variables in the initial group and added variables from groups in Table 2 that did not have a variable included in the current set. This iterative process expanded the core set of variables when an additional factor yielded a coefficient with the correct sign, statistical significance, and improved classification accuracy. Further, this approach concentrates on the explanatory power of variables and helps avoid multicollinearity. The selection of the final set of financial and operating ratios was based on the statistical significance and direction of estimated parameters and on the model's classification accuracy. It was expected that financial distress would be positively related to financial leverage, but negatively related to profit margin, profitability, liquidity, cash position, growth, and operation efficiency.

TABLE 3. PRIVATE VS. PUBLIC FIRMS: DESCRIPTIVE STATISTICAL COMPARISON ($000S)

	Mean Private Firms	Mean Public Firms	t-test *p*-value	Median Private Firms	Median Public Firms	χ^2 Median test *p*-value
Income Statement Item						
Net Sales	1508.102	499.888	0.337	26.237	180.581	<.005
Depreciation and Amortization	48.445	17.998	0.398	1.175	5.842	<.05
Net Income	69.786	6.627	0.186	0.083	4.346	<.05
Balance Sheet Item						
Current Assets	529.559	188.019	0.378	6.276	52.261	<.025
Net Fixed Assets	262.333	131.155	0.477	7.193	37.928	<.025
Total Assets	987.791	406.007	0.412	12.262	109.567	<.005
Notes/Payable	14.053	19.865	0.707	2.453	0.001	<.05
Current Liabilities	367.611	111.939	0.394	7.978	29.304	ns
Long Term Debt	180.293	108.877	0.592	2.756	13.865	<.05
Shareholders' Equity	310.255	129.336	0.345	1.787	53.052	<.005
Calculated Item						
EBITDA	173.862	50.681	0.308	1.196	17.680	<.025
Net Cash Flow	118.231	24.625	0.260	0.822	9.296	<.025
Net Cash Flow (lagged one period)	108.767	28.565	0.288	1.229	8.832	<.025

Statistical Analysis

Logit regression analysis was used to estimate the parameters of the model. Logit regression has been shown to provide flexibility and statistical power when modeling (McFadden 1984; Lo 1986). Further, a recent test that directly compares logit regression to other modeling techniques has shown that logit regression results dominate those produced by neural networks (Yang, Platt, and Platt 1999). By contrast, Barniv et al. (1997), Boritz and Kennery (1995), and Zhang et al. (1999) preferred neural networks over other model formats. A non-linear maximum-likelihood estimation procedure was used to obtain estimates of the parameters of the logit model shown in equation (1).

$$P_i = 1/[1 + \exp -(B_0 + B_1X_{i1} + B_2X_{i2} + \ldots + B_nX_{in})] \qquad (1)$$

where: P_i = probability of financial distress of the *i*th firm, and
X_{ij} = *j*th variable of the *i*th firm.

Choice-Based Sample Bias Test

Because it has been alleged that choice-based sample bias creates problems when a group is over-represented in a sample, seven test samples were formed by successively reducing the number of included healthy companies until eventually a nearly matched sample was left. Total sample sizes varied from 85 companies down to just 56 companies. For each sample size, 50 regressions were run using the final model specification. The 50 regressions were based on all 24 financially distressed firms and a randomly selected set of healthy firms. To test for choice-based sample bias, the mean estimated coefficient across 50 logit regressions are statistically compared to the population parameter.

Bias exists when the mean estimated coefficient, $\hat{\beta}$, is significantly different from the population parameter, β, as shown in equation (2).

$$\text{Bias} = (\hat{\beta} - \beta)/\sigma_{\beta} \qquad (2)$$

The mean estimated coefficient is obtained by averaging individual estimated coefficients across the 50 simulations. Both the population parameter coefficient and the standard error for that coefficient are taken from estimates obtained in the final model based on the population of all automotive suppliers.

An alternative form of this test, used in this study, examines whether $\hat{\beta}$ falls within the 95 percent confidence interval estimate for β. The mean estimated coefficient is not statistically different from the parameter if $\hat{\beta}$ falls within the confidence interval. A second approach used to examine bias records the percentage of the individual estimated coefficients for the 50 simulations that fall within the confidence band.

Finally, Zmijewski (1984) argued that choice-based bias would be present if there were a significant correlation between the proportion of the sample that was bankrupt and the correct classification results for each group considered separately. Specifically, he hypothesized that one should find a positive relationship between the sample bankrupt proportion and the correct classification rate for the bankrupt group, but a negative relationship between the sample bankrupt proportion and the correct classification rate for the nonbankrupt group. His reported results were consistent with the first expectations for the bankrupt group classification rates, but were mixed for the nonbankrupt group. Again, Zmijewski's analysis was based on only one regression for each sample proportion. We replicate his test using results from the 50 regressions based on randomly configured samples, varying in the proportion of financially distressed to healthy companies.

Results

Early Warning System Model

The final model contains six variables: one indicating profit margin, two measuring liquidity, two assessing leverage, and one designating growth. The specific variables, the scaled estimated coefficient,[4] and the resulting t-statistics for the final model are shown in Panel A of Table 4. Healthy companies were arbitrarily coded as 0, while financially distressed firms were coded as 1. Therefore, a negative coefficient indicated an inverse relationship to financial distress, whereas a positive coefficient indicated a direct relationship to financial distress. As shown in Table 4, a company is more likely to suffer financial distress if it had lower (or negative) operating cash flow to sales, a lower current ratio, higher net fixed assets to total assets, higher long-term debt to equity, higher notes payable to total assets, and lower (or negative) cash flow growth from last period. It appears that cash flow level and growth are important predictors of financial distress as well as liquidity, commitment to long-term assets, and debt (both long-term and short-term).

[4] The estimated coefficients are not presented since they are the property of BBK, Ltd. The estimated coefficients have been scaled to show their sign and relative size.

TABLE 4. FINAL EARLY WARNING MODEL TO PREDICT FINANCIAL DISTRESS

Panel A. Variables in the Final Early Warning Model

Variables	*Scaled Coefficient**	*p-value (one-tail)*
EBITDA/S	-28.74	.035
CA/CL	-4.62	.076
NFA/TA	48.51	.043
LTD/EQ	18.57	.073
NP/TA	14.34	.042
CF-Growth %	-16.75	.104
Constant	2.95	.304

Panel B: Model Classification Results

Classification Group	*Percent Correctly Classified*
Financially Distressed Firms (n = 24)	92%
Healthy Firms (n = 62)	100%
All Firms (n = 86)	98%

Panel C: Validation Test Classification Results

Classification Group	*Percent Correctly Classified*
Financially Distressed Firms (n = 5)	100%
Healthy Firms (n = 4)	100%
All Firms (n = 9)	100%

Note: * Coefficients are scaled. Estimated coefficients are the property of BBK, Ltd.

The model had an overall correct classification rate of 98 percent, as shown in Panel B of Table 4. For the distressed group, the model correctly classified 92 percent of companies; for the non-distressed group, 100 percent of companies were correctly classified. The model was also subjected to subsequent testing based on private company data supplied by BBK Ltd. The test involved inputting data on nine companies not in the estimation sample. It was run blind; that is, BBK Ltd. did not reveal the status of the test companies in advance of the test. As shown in Panel C of Table 4, this validation test indicates that the model is as accurate in the application of post model building stage as it was during the model building effort. Of nine companies tested, all were correctly classified.

Tests of Choice-Based Sample Bias

To test for choice-based sample bias, several sample sizes were delineated ranging from one less than the entire population of firms (n=85) to a sample of 56 firms.[5] Logit regressions were run based on 50 random samples composed of all distressed firms and different healthy firms selected randomly from the entire set of healthy firms. For each of the six variables in the model and the constant term, the mean estimated coefficient was statistically compared across the 50 regressions

[5] With fewer than 56 firms in the sample, it was impossible to run 50 randomly sampled regressions.

for each sample size to the population parameter. Bias exists when the mean estimated coefficient is significantly different from the population parameter. Additionally, the percentage of individual estimated coefficients falling within the 95 percent confidence interval around the population parameter were recorded. Results are shown in Table 5 for the varying samples constructed.

The simulation results in Table 5 show that the existence of bias increases as the proportion of financially distressed firms to healthy firms becomes more evenly matched. First, across all coefficients and the constant term, the mean estimated coefficient value of the 50 regressions, $\hat{\beta}$, falls out of the 95 percent confidence interval for β after a modest drop in the sample proportion of financially distressed to healthy firms. Second, the percentage of the individual estimated coefficients that fall within the confidence interval drops from the high 90s to the mid-teens as the sample becomes more evenly matched.

TABLE 5. CHOICE-BASED SAMPLE BIAS TESTS

	EBITDA/S	CA/CL	NFA/TA	LTD/EQ	NP/TA	CF-Growth	CONSTANT	Classification Rates: Distressed Firms
			Sample Size: n = 85 (1:2.54)					
% in CI	97%	97%	98%	98%	98%	98%	97%	92%
$\hat{\beta}$ in 95% CI for β	In	In	In	In	In	In	In	correct
			Sample Size: n = 80 (1:2.33)					
% in CI	88%	88%	94%	86%	92%	92%	88%	92.2%
$\hat{\beta}$ in 95% CI for β	Out	Out	In	Out	Out	Out	In	correct
			Sample Size: n = 77 (1:2.21)					
% in CI	40%	40%	54%	44%	52%	44%	42%	95.5%
$\hat{\beta}$ in 95% CI for β	Out	Out	Out	Out	Out	Out	Out	correct
			Sample Size: n = 71 (1:1.96)					
% in CI	42%	40%	54%	44%	50%	42%	40%	95.5%
$\hat{\beta}$ in 95% CI for β	Out	Out	Out	Out	Out	Out	Out	correct
			Sample Size: n = 65 (1:1.71)					
% in CI	34%	36%	40%	26%	40%	34%	36%	97.0%
$\hat{\beta}$ in 95% CI for β	Out	Out	Out	Out	Out	Out	Out	correct
			Sample Size: n = 60 (1:1.50)					
% in CI	16%	18%	24%	14%	22%	16%	20%	98.2%
$\hat{\beta}$ in 95% CI for β	Out	Out	Out	Out	Out	Out	Out	correct
			Sample Size: n = 56 (1:1.33)					
% in CI	16%	16%	24%	22%	14%	16%	20%	98.5%
$\hat{\beta}$ in 95% CI for β	Out	Out	Out	Out	Out	Out	Out	correct

Note: "In" indicates that the mean estimated coefficient for the fifty regressions, $\hat{\beta}$, fell within the 95 percent confidence interval for β. "Out" indicates that $\hat{\beta}$ fell outside of this interval.

Further, Zmijewski (1984) argued that a positive correlation between the percentage of the sample in the bankrupt group and the correct classification of bankrupt firms would indicate bias. A similar correlation was tested for these data. The Pearson correlation coefficient measuring the degree of relationship between the percentage of the sample that is financially distressed firms and the correct classification rate for financial distressed firms was .936, which was significant beyond the .005 level. A similar analysis of the correlation between the sample proportion of financially distressed firms and the correct classification rate for the healthy firms yielded an $r = -.10$, which was not statistically significant. Both findings are consistent with Zmijewski's expectations and his empirical findings for the alternative estimation samples. Hence, the percentage accuracy reported for distressed companies is misleading since by changing sample proportion weights the model classification percentages are slanted toward the distressed quadrant and away from the population. Therefore, analysts who use outputs from early warning system models must proceed cautiously; they may have inflated confidence in a model's predictive accuracy if the model is constructed using a sample that differs substantially from the population's proportion of distressed to healthy firms.

Conclusion

An early warning system model was built to predict financial distress, not bankruptcy, among firms in the automotive supplier industry. The automotive industry is a good example of supply chain management because the primary automotive equipment manufacturer no longer fabricates most of the automotive parts that make up the finished automobile. This relationship has motivated several large automobile manufacturers to pay close attention to the financial condition of their primary suppliers. To the extent that other manufacturing industries rely on vendors in their supply chain, they may benefit from early warning system models that can help forecast future financial distress. Predictions of future problems can help all parties rectify problems before they disrupt production or delivery of product.

Our interest was not in bankruptcy since that would be too late to ameliorate supplier disruptions. Firms were classified as financially distressed if they reported several years of negative net operating income, suspended their dividends, or were clients of a turnaround-consulting firm that specializes in the automotive supplier industry. All public and some private firms in the industry were included in the analysis. We interpreted this group of firms as the population of automotive suppliers.

A logit regression analysis produced a model that contained six factors: EBITDA to Sales, Current Assets to Current Liabilities, Net Fixed Assets to Total Assets, Long-Term Debt to Equity, Notes Payable to Total Assets, and the one-year Cash Flow Growth Rate. The first two factors, EBITDA to Sales and Current Assets to Current Liabilities, and the last one, the annual Cash Flow Growth Rate, were negatively related to the probability that a firm would experience financial distress. Thus, the larger these ratios, the less likely a firm would experience financial distress. The other three factors, Net Fixed Assets to Total Assets, Long-Term Debt to Equity, and Notes Payable to Total Assets, were positively related to financial distress. For these variables, the larger the ratio, the more likely that a firm suffers from financial distress. The final model correctly classified 98 percent of all firms in the population, resulting from correctly classifying all of the healthy firms and 92 percent of the financially distressed firms. A validation test correctly classified all firms, both healthy and financially distressed.

Most prior early warning system research has modeled bankruptcy because the time at which the filing occurs is generally known. Arguably, there is greater value taking a normative perspective to avoid bankruptcy by identifying financial distress while corrective actions may modify ultimate outcomes. Our work demonstrates that identification of early financial distress targets is not only feasible but a practical goal as well. The model benefits automobile manufacturers who can now advise or take early actions to reduce the number of their suppliers who encounter crises; intervention during the late stages of financial distress should reduce the number of these firms entering bankruptcy.

The study also empirically tested the argument that early warning system models need to include all firms within a population; otherwise, choice-based sample bias could result. The simulation results show evidence that choice-based sample bias increases as the proportion of financially distressed to healthy firms within a sample increases. Most notably, when a matched sample design is used in 50 random regressions, fewer than one in five coefficient estimates is within a 95 percent confidence band around the true population parameter. Thus, sample design can negatively affect the results of early warning system models that are not built using the population. This information may help other researchers choose their sample characteristics.

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