EVALUATION OF A FINANCIAL DISTRESS MODEL
FOR DEPARTMENT OF DEFENSE HARDWARE CONTRACTORS

by

Richard B. Collins, II

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APPROVED:

David I. Meiselman , Chairman

William R. Porter

Nancy N. Wentzler

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(ABSTRACT)

This thesis investigates the accuracy of a model that the Department of the Navy uses to predict the financial health of major defense hardware contractors. The inputs to this model are six financial ratios derived from a firm's income sheet and balance statement. The output of this model is a single Z-score that indicates the health of a firm. Depending on the score, a firm's financial standing is classified as healthy, distressed or uncertain.

The model is tested using a database compiled for this thesis that includes financial information for a total of 72 defense and non-defense firms. The test database is unique relative to the underlying model database; it reflects a more recent timeframe and a greater number of firms, none of which were used to develop the model.

Model accuracy was <u>computed</u> by measuring how often the model correctly classified a bankrupt firm as distressed and a nonbankrupt firm as healthy. Then, model <u>accuracy</u> was

evaluated by comparing these test results (i.e., percent correctly classified) to results published by the model's developers. This comparison produced mixed results. In light of this fact, the thesis concludes that the model should be improved and recommends a course of action.

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CHAPTER 1

INTRODUCTION

Financial distress occurs when a firm is either unable to meet its contractual obligations to creditors or is able to do so only with difficulty.[1] Sometimes the outcome of financial distress is bankruptcy. Sometimes the outcome is a firm that "skates on thin ice". This thesis is concerned with predicting the former outcome for Department of Defense (DOD) hardware contractors.[2]

Corporate bankruptcy and its prediction received a great deal of attention during the 1970s and 1980s. In the 1970s, an average of 25,891[3] firms a year petitioned the courts to liquidate or reorganize under the protection of the United States' bankruptcy laws. In the 1980s, this average increased

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[1]Financial distress is also known as financial failure. See Engler (1978) for a discussion of financial failure.

[2]For the purpose of this thesis, bankruptcy is defined as the formal legal proceeding through which a firm seeks a remedy to its financial distress either in the form of liquidation or reorganization. See Altman (1971,1983) and Weintraub (1980) for discussions of bankruptcy and reorganization theory and the bankruptcy process.

[3]The source of all the statistics presented in this paragraph is Administrative Office of the U.S. Courts, Annual Report of the Director. This information was compiled in U.S. Department of Commerce, Statistical Abstract of the U.S., 1981 and 1991.

nearly 150 percent to 64,414 firms per year. These statistics reflect the failure of not only small, undercapitalized businesses but also corporate giants such as Penn Central, Braniff and Manville. The number of firms filing petitions in 1990 and 1991 were 64,688 and 67,714, respectively. These numbers represent increases over the preceding year of three and five percent, respectively. The state of the economy and bankruptcy announcements by TWA and Macy's early in the year are signs that the trend will continue in 1992.

The upward trend in bankruptcies over the last 22 years suggests that tools are needed to periodically evaluate a firm's financial condition. From an internal control perspective, these tools should allow corporate management to identify problems early enough to implement corrective measures and thereby avoid potential failure. From an investment point of view, these tools should enable an existing or prospective investor to assess the feasibility of a given investment. Accordingly, since the late 1960s, researchers have developed a number of similarly structured tools (i.e., models) for evaluating the financial health of firms representing different industries, including railroad, banking, manufacturing and retail.[4]

Though few major Department of Defense (DOD) contractors have ever declared bankruptcy, these firms and the smaller firms operating as subcontractors and suppliers are not immune to financial distress. The government bailout of such major DOD hardware contractors as Lockheed and Chrysler together with the collapse of major DOD contractors such as LTV and Todd Shipyards are proof that bankruptcy is a real threat to large corporate structures with vital national defense capabilities. The potential national defense implications of bankruptcy are extremely serious and include: 1) reduction in the number of qualified producers (i.e., smaller industrial base); 2) lower product quality due to either fewer qualified firms or cost cutting measures driven by a firm's poor financial condition; and 3) less timely delivery of products. In light of these implications, the Department of the Navy (DON) developed and is currently using a model to evaluate and predict the financial health of hardware contractors.[5] Similar in design to the previously developed models, this

[4]See Chapter 2 of this thesis for descriptions of several existing models. Also see Altman (1983) for a more exhaustive review of these and other models.

[5]See Dagel and Pepper (1990). It should be noted that the model was completed in late 1988 but not published until early 1990.

financial distress, or "Z-score"[6], model provides a single quantitative measure of a firm's financial health which is used to classify a firm as to likelihood of bankruptcy.

DON management has used the model for at least three purposes. First, the model has been used to assess the effects of competition on corporate entities. There has been much debate over the impact of competition on the total price the Navy pays for weapon systems during production. That is, does competition result in savings or added costs? If so, how much?[7] Past Navy competitions for commodities such as missiles, torpedoes and ships have often been characterized by aggressive contractor bidding that resulted in apparent savings to the service. While government savings is important, so too is the financial health of the competing contractors. To explain, vigorous competition for limited defense dollars has in many cases led the Navy to award contracts for optimistically low prices. Unfortunately, the

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[6]The first and most well known multivariate bankruptcy prediction model was called the Z-score model (see Altman 1968). Since then, it has been commonplace for subsequent bankruptcy prediction models to be labelled as Z-score models.

[7]There is an extensive body of literature that addresses the effect of competition on weapon system prices, including empirical studies that use alternative techniques to measure the dollar savings (or losses) associated with past competitions. For example, among others, see two past Virginia Polytechnic Institute and State University Master's theses - Falk (1991) and Maxwell (1988).

fixed-price nature of these contracts has forced contractors that "bought-in" to absorb cost overruns alone. This, in turn, may negatively impact the financial condition of the firm and have the same serious implications identified in the preceding paragraph. In this case, the Z-score model has been used to determine the extent to which a contractor can/cannot absorb losses and the ability of the firm to compete in the future.

Second, the model has been used to formulate acquisition strategies. Prior to initiating the acquisition (i.e., development and production) of a new weapon system, the Navy formulates a plan of action and milestones, or acquisition strategy, for achieving the service's ultimate goal - a fielded system that performs as designed. Among other details, the Navy's acquisition strategy typically identifies the number of contracts to be awarded to industry.[8] Analysis of the participating contractors' financial health (past, current and projected) with the Z-score model may be a valuable input in designing/executing an effective acquisition strategy. For example, financial health projections may

[8]For example, the DDG 51 shipbuilding program has followed an acquisition strategy that called for annual buys of three-to-five ships to be split via annual competitions between two shipyards - Ingalls Shipbuilding Division and Bath Iron Works.

indicate future contractor problems that could jeopardize the timely delivery of systems.

Third, and directly related to the first purposes, the model has been used to assist in awarding and negotiating contracts. Defense contracts have typically been awarded to those firms that offer the best value to the government in terms of technical approach/capability and price. However, Navy contract award criteria have been known to vary with the specific goals of the award at hand. For example, if lowest price is the Navy's goal, then the overriding concern is price. Conversely, if the Navy's goal is to maintain or expand the industrial base, then technical expertise may be the key criterion. The financial health indicator provided by the Z-score model may represent another criterion that should be considered during a contract award decision. That is, if lowest price is the goal, then a firm which is experiencing or close to financial distress is a risky candidate. Conversely, if industrial mobilization is the goal, then this same firm may be a good candidate in that the Navy could prolong the firm's life through a contract award.

The objective of this thesis is to evaluate the accuracy of the Z-score model currently employed by the Navy. The output of this model is a single score that indicates the health of a firm: Z > 2.45 means healthy, Z < 0 means distressed and Z between 0 and 2.45 means uncertain health. The model was based on discriminant analysis of a database that includes historical financial information for 29 nonbankrupt (i.e., healthy) and 29 bankrupt (i.e., distressed) manufacturing firms covering the period 1982 to 1986.[9]

This thesis tests the DOD model's accuracy as follows. First, a new historical database of 36 nonbankrupt and 36 bankrupt manufacturing firms covering the period 1987 to 1991 was compiled. None of these firms were included in the original (i.e., 58 firm) database. Then, a Z-score was computed for each new firm. Next, each of the 72 Z-scores was evaluated for classification accuracy, i.e., how often did the model classify a bankrupt firm as nonbankrupt and vice versa? Then, the 72 Z-scores were used to compute separate mean Z-scores for the bankrupt and nonbankrupt samples. These mean Z-scores were compared to the counterpart means for the original database. The differences were identified and potential explanations were offered.

This thesis is organized as follows. Chapter 2 discusses the relevant literature that supported development of the DOD

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[9]The mean Z-score is 2.45 for nonbankrupt firms and -2.45 for bankrupt firms.

Z-score model. Specifically, it describes the predominant statistical methodology (i.e., discriminant analysis) employed by bankruptcy prediction models, including the DOD Z-score model, and reviews some of the other bankruptcy prediction models. This chapter not only sets the scene for describing the DOD Z-score model but also contributes to the model evaluation approach. Chapter 3 describes in detail the DOD Z-score model and the evaluation conducted for the thesis. The framework for evaluating this model parallels, where possible, the overall model development approach employed by Dagel and Pepper. Finally, Chapter 4 presents my conclusions and recommendations.

CHAPTER 2

PREDICTING CORPORATE BANKRUPTCY

The development of empirical models that discriminate between bankrupt and nonbankrupt firms is an important accomplishment of modern finance.[10] The DOD Z-score model is an extension of a body of previous works in the field. This chapter describes the statistical analysis technique that is predominant in the bankruptcy prediction field and underlies the DOD Z-score model. This chapter also characterizes several bankruptcy prediction models developed since the mid-1960s.

2.1 Discriminant Analysis

Discriminant analysis is a multivariate statistical technique that has been used successfully to develop several previous bankruptcy prediction models. Introduced by Fisher in the 1930s to address plant taxonomy problems[11], discriminant analysis is used to classify an observation into one of several a priori groups dependent upon the

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[10]This is the stated or implied opinion of a variety of authors who have either developed or used bankruptcy prediction models, including Altman (1983), Engler (1978) and Scott (1981), among others.

[11]See Fisher (1936)

observation's individual characteristics. The groups, or dependent variable, are typically qualitative in nature (e.g., bankrupt and nonbankrupt firms). The characteristics, or independent variables, are quantitative in nature (e.g., financial ratios such as total debt-to-total assets, etc.). Several example bankruptcy classification problems that discriminant analysis has been applied to are identified in Table 2-1.

Fisher proposed that we consider a linear discriminant function of the form $Y = V_1X_1 + V_2X_2 + \ldots + V_nX_n$ where:

$V_1, V_2, \ldots, V_n$ = discriminant coefficients and

$X_1, X_2, \ldots, X_n$ = independent variables.

The total sum of squares of this linear function can then be broken up into two parts, a part with n_1 degrees of freedom which is the between means of groups sum of squares and a part with n_2 degrees of freedom which is the within groups sum of squares. The coefficients of the linear function of the Xs are chosen so that the ratio of the between means of groups sum of squares to within groups sum of squares is maximum. This ratio can be used as a basis for a test of the hypothesis that the two points representing the position of the n means

Table 2-1
Example Bankruptcy Classification Problems[*]

Groups	Characteristics
A. Bankrupt and nonbankrupt railroads	1) cash flow/fixed charges 2) earned surplus/total assets 3) transportation expenses/revenues 4) 3 year growth rate in revenues 5) earnings after taxes/revenues 6) operating expenses/revenues 7) earnings before interest and taxes/total assets
B. Serious-problem, temporary-problem and no-problem savings and loan associations	1) net operating income/gross operating income 2) net worth/total assets 3) real estate owned/total assets 4) earned surplus/total assets 5) total loans/total savings 6) borrowed money/total savings 7) FHLB advances/net worth 8) two-period trend of 1 9) two-period trend of 2 10) two-period trend of 3 11) two-period trend of 3 for scheduled item real estate 12) two-period trend of 6
C. Bankrupt and nonbankrupt property-liability insurers	1) agents balances/total assets 2) stocks-cost/stocks-market 3) bonds-cost/bonds-market 4) sum of loss adjustment expenses paid and underwriting expenses paid/net premiums written 5) "combined" (i.e., underwriting profitability) ratio 6) premiums written direct/surplus
D. Bankrupt and nonbankrupt manufacturers	1) Various financial ratios

[*]See Altman (1983) for examples A and B. See Trieschmann and Pinches (1972) for example C. See the next section (2.2) for several examples of example D.

of the groups in the n dimensional space occupy the same point for the populations under consideration. The linear function of the X variables that maximizes the ratio of the between means of groups sum of squares to within groups sum of squares and minimizes the likelihood of misclassification is the discriminant function.

Three key assumptions of this linear function are that: 1) variables describing the members of the group observations are multivariate normally distributed within each group; 2) group covariances are equal across all groups; and 3) groups are discrete, nonoverlapping and identifiable.

According to bankruptcy prediction literature[12], there are at least two advantages of discriminant function analysis. The first advantage is the reduction of the analyst's space dimensionality, i.e., from the number of different independent variables to G-1 dimension(s), where G equals the number of original a priori groups. Therefore, if the analysis is concerned with two groups (e.g., bankrupt and nonbankrupt firms), then the analysis is transformed into its simplest form - one dimension. The discriminant function (Y) transforms the individual variable values to a single

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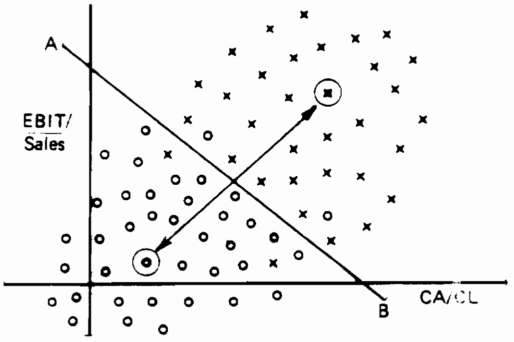
[12]See Altman (1983), among others

discriminant score (e.g., Z) which is then used to classify the observation as bankrupt or nonbankrupt.

Second, due to its multivariate nature, discriminant analysis has the advantage of considering an entire profile of characteristics common to the observation being classified, as well as the interaction of these properties.[13] The bottom line is that discriminant analysis enables a problem to be reduced from one of understanding many different variables individually to combining the variables into a single variable or score.

Figure 2.1, excerpted from Altman (1983), is an example two-group classification via discriminant analysis. For a



* EBIT = earnings before interest and taxes; CA = current assets; CL = current liabilities; O = bankrupt firms; X = nonbankrupt firms; circled O and X = group means

Figure 2.1 Linear Discriminant Analysis: An Example*

[13]In contrast to a univariate study which can only consider one variable at a time and ignores possible interdependencies with other variables.

hypothetical two variable (i.e., financial ratio) discriminant function, the variable space is divided into two half-plane classification regions representing nonbankrupt and bankrupt firms. The region greater than or equal to (i.e., to the right of) the dividing line (AB) represents nonbankrupt firms while the region less than or equal to (i.e., to the left of) the line represents bankrupt firms. The discriminant model selects the appropriate weights which will separate as far as possible the average values of each group while at the same time minimizing the statistical difference of each observation (the individual Xs and Os) and its own group mean (i.e., the model maximizes the between-group to within-group variance). Each observation is then "projected" on the line (AB) which best discriminates between the two groups.

2.2 Existing Financial Distress Models

The modern use of financial ratios to predict bankruptcy was pioneered in papers by Beaver[14] and Altman[15]. This section describes these path-breaking works in addition to two (of numerous) other studies that have attempted to improve upon and extend the bankruptcy classification problem.

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[14]See Beaver (1967 and 1968)

[15]See Altman (1968) and Altman, Haldeman and Narayanan (1977)

2.2.1 Beaver (1967)

Data Sample

This paper represents the first modern statistical evaluation of models to predict financial failure. While most subsequent researchers have investigated only bankruptcies, Beaver used a broader definition of failure, i.e., inability of a firm to meet financial obligations as they mature. His sample of 79 failed firms included 59 bankruptcies, 16 preferred stock dividend arrearages, three bond defaults and one overdrawn bank account. Having "failed" during the period 1954 to 1964, the firms represented 38 different industries and the average firm had approximately $6 million in assets (based upon the most recent balance sheet prior to failure). The asset size range was $0.6 to $45 million. For every failed firm in the sample, there is a nonfailed firm (i.e., 79) from the same industry and approximately the same asset size class.

Beaver collected five years of financial data for each of the 158 firms from Moody's Industrial Manual. For failed firms, data were collected for the five years preceding the failure year. For nonfailed firms, it appears that data covering the same period (1954 to 1964) were compiled for randomly selected firms. These data were used to compute 30 different financial ratios.[16] The ratios were selected on the basis of three criteria: 1) popularity in the literature; 2) performance in previous studies; and 3) definition of the ratio in terms of a "cash flow" concept. On the basis of lowest percentage prediction error (in dichotomous classification tests) for each group over the five-year period, Beaver selected the following six variables as "best": 1) cash flow to total debt; 2) net income to total debt; 3) cash flow to total assets; 4) current plus long-term liabilities to total assets; 5) working capital to total assets; and 6) no-credit interval.

Empirical Approach and Results

Beaver's study applies a univariate approach, not multivariate discriminant analysis.[17] Beaver conducted three major empirical experiments: 1) comparison of mean values; 2)

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[16]In a subsequent study, Beaver used the same database to analyze a subset (i.e., 14) of these 30 ratios. See Beaver (1968). Deakin (1972) evaluated these 14 ratios using discriminant analysis.

[17]Although discriminant analysis has been the statistical technique of choice in the development of bankruptcy prediction models, Beaver's univariate analysis deserves attention in this thesis because it led subsequent researchers (i.e., Altman, Deakin and others) to investigate the predictive ability of combinations (vice single) of ratios through discriminant analysis.

dichotomous classification tests; and 3) analysis of likelihood ratios. He found the anticipated differences in the mean values for each of the six ratios in all five years before failure. In addition, the average failed firm showed substantial deterioration as the year of failure approached. In contrast, the performance of the average nonfailed firm was relatively constant with only small deviations from trend.

Beaver's classification test involved a dichotomous prediction or binomial response (i.e., failure or nonfailure). To make the predictions, Beaver arranged each of the 30 ratios (for both failed and nonfailed firms) in ascending order. Next, he visually inspected each pair of arrays to find the cutoff point that minimized the percentage of incorrect predictions. If a firm's ratio was below the cutoff ratio, the firm was classified as failed. Conversely, if the firm's ratio was above the cutoff point, the firm was classified as nonfailed. Beaver compared the classifications to the actual status (i.e., failed or nonfailed) of the firms and computed the percentage of correct classifications. He used this percentage as a crude index of a ratio's predictive ability.

Beaver's results suggested that single financial ratios can predict failure quite well at least five years in advance. Based on his findings, Beaver concluded that the cash flow/total debt ratio was the best predictor of the 30 ratios. Table 2-2 identifies the classification accuracy of this ratio. The first value represents the ratio's

Table 2-2
Beaver Model Classification Accuracy

Years Prior To Failure	% Correct Failed Sample
1	90(87)
2	82(79)
3	79(77)
4	76(76)
5	78(78)

classification accuracy for the original failed firm sample while the value in parenthesis is accuracy for a "holdout"[18] sample. These results indicate that the cash flow/total debt ratio was able to accurately classify 78 percent of either failed firm sample five years before failure and 87-to-90 percent of these same samples one year prior to failure.

2.2.2 Altman (1968)

Following Beaver (1967), most researchers have felt that basing bankruptcy prediction models on a single financial

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[18]The composition of Beaver's "holdout" sample is not well documented but appears to be a subset of the original 158 firm sample.

ratio is too simplistic to capture the complexity of financial failure. As a result, many subsequent works have used multiple discriminant analysis to derive prediction formulas that include combinations of ratios. The first and most well known of these research efforts was Altman's Z-score model. Having received a good deal of exposure in finance texts and in non-academic publications, this model has been a standard of comparison for subsequent bankruptcy classification studies.

Data Sample

The model data sample was composed of 66 corporations. Half were manufacturers that filed for bankruptcy under Chapter X[19] of the National Bankruptcy Act during the period 1946 to 1965. The mean asset size of these firms was $6.4 million with a range of between $0.7 and $25.9 million. The other half of the data sample was nonbankrupt firms representing a paired sample of manufacturing firms selected on a stratified random basis. The firms were stratified by

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[19]Prior to October 1979, federal bankruptcy laws provided for two types of corporate bankruptcy reorganizations: the Chapter X proceeding and the Chapter XI arrangement, where the former generally involved larger and more important firms than the latter. Subsequent federal law has eliminated the distinction and consolidated bankruptcy reorganizations into Chapter 11 of the bankruptcy code. See Altman (1983) for a further discussion.

industry and by size, with the asset size range restricted to between $1 and $25 million. The mean asset size of the nonbankrupt sample ($9.6 million) was larger than the bankrupt sample but Altman did not consider this a problem. Firms in the nonbankrupt set were still in existence in 1966.

The specific information collected for the entire sample were balance sheet and income statement data from Moody's Industrial Manual and selected annual reports. Altman compiled five years of data for each firm. For bankrupt firms, data were collected for the five years preceding the year in which a firm filed for bankruptcy. For nonbankrupt firms, it is unclear which five years were selected for data collection.

Because of the large number of variables found to be significant indicators of corporate problems in past studies, a list of 22 potentially helpful variables (i.e., financial ratios) were derived from the data collected. The variables were classified into five standard ratio categories - liquidity, profitability, leverage, solvency and activity. The ratios were chosen on the basis of past studies' findings that they were significant indicators of corporate problems. Beaver (1967) concluded that the cash flow to debt ratio was the single best ratio predictor. However, Altman chose to exclude this ratio because of the lack of consistent and precise depreciation data.

Empirical Approach and Results

Based on discriminant analysis of one year of data per firm[20], Altman selected a linear combination of five of the 22 variables as the best bankruptcy predictor. The resulting discriminant function was:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

where

X_1 = working capital/total assets;
X_2 = retained earnings/total assets;
X_3 = earnings before interest and taxes (EBIT)/total assets;
X_4 = market value equity/book value of total liabilities;
X_5 = sales/total assets; and
Z = overall index (i.e., Z-score).

In order to arrive at the final profile of five variables, Altman used the following procedures: 1) observation of the statistical significance of various

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[20]That is, the year prior to bankruptcy for bankrupt firms and a randomly selected year for nonbankrupt firms were analyzed. The remaining fours years of bankrupt firm data were used to test the model (see Table 2-5) while the remaining nonbankrupt firm data was not used.

alternative functions including determination of the relative contributions of each independent variable; 2) evaluation of intercorrelations among the relevant variables; 3) observation of the predictive accuracy of the various profiles; and 4) analytical judgement.

An F-test was performed to test the individual discriminating ability of the variables. This test relates the difference between the average values of the ratios in each group (bankrupt and nonbankrupt) to the variability (or spread) of values of the ratios within each group. Variable means measured at one financial statement prior to bankruptcy and the resulting F-statistics are presented in Table 2-3.

Table 2-3
Variable Means and Test of Significance

Variable	Bankrupt Mean*	Nonbankrupt Mean*	F Ratio
X_1	-6.1%	41.4%	32.60
X_2	-62.6%	35.5%	58.86
X_3	-31.8%	15.4%	26.56
X_4	40.1%	247.7%	33.26
X_5	1.5X	1.9X	2.84

* n=33

Variables X_1 through X_4 are all significant at the 0.001 level, indicating extremely significant difference in these variables among groups. Conversely, variable X_5 does not show a significant difference among groups. On a strictly univariate level, all of the ratios indicate higher values for the nonbankrupt firms. Also all of the discriminant coefficients display positive signs. As such, the greater a firm's bankruptcy potential, the lower its discriminant (i.e., Z) score.

In order to arrive at the final variable profile, Altman determined the relative contribution of each variable to the total discriminating power of the function, and the interaction between them. This was accomplished by considering the scaled vector of each variable, which was computed by multiplying corresponding elements of the square roots of the diagonal elements of the variance-covariance matrix.[21] Since the actual variable measurement units were not all comparable to each other, simple observation of the discriminant coefficients was misleading. Accordingly, the adjusted coefficients shown in Table 2-4 enabled Altman to evaluate each variable's contribution on a relative basis.

[21]For example, the square root of the appropriate variance-covariance figure (standard deviation) for X_1 is approximately 275 and when multiplied by the variable's coefficient (.012) yields a scaled vector of 3.29.

Table 2-4
Relative Contribution of the Variables

Variable	Scaled Vector	Ranking
X_1	3.29	5
X_2	6.04	4
X_3	9.89	1
X_4	7.42	3
X_5	8.41	2

The scaled vectors indicate that the large contributors to group separation of the discriminant function are X_3, X_5 and X_4, respectively. According to Altman, it was not surprising that the profitability ratio (EBIT/total assets, or X_3) was the largest contributor, since profitable firms rarely experience bankruptcy. However, it was surprising that X_5 (sales/total assets) was the second highest contributor, especially since this ratio was insignificant on a univariate basis (see Table 2-3).[22] Altman attributed this unexpected result to the high negative correlation (-.78) demonstrated between X_3 and X_5 in the bankrupt sample.[23]

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[22]See Cooley and Lohnes (1962) for a discussion of how an apparently insignificant variable on a univariate basis can provide important information in a multivariate context.

[23]See Cochran (1964) for an evaluation of the discriminant function that concluded that most correlations between variables in past studies were positive and that, by and large, negative correlations were more helpful than positive correlations in adding new information to the function.

Having demonstrated that four of the five variables display significant differences between groups, Altman conducted an F-test to determine the overall discriminating power of the model. The F-value is the ratio of the between groups sum of squares to the within groups sum of squares. When this ratio is maximized, it has the effect of spreading the means of the groups apart and, simultaneously, reducing dispersion of the individual points (i.e., firm Z-scores). This test was appropriate because the objective of discriminant analysis is to identify and utilize those variables which best discriminate between groups and which are most similar within groups. The group means of the two-group sample were:

Bankrupt = -.29 $\quad F = 20.7$

Nonbankrupt = 5.02 $\quad F_{5.60}\ (.01) = 3.84$

The significance test therefore rejected the null hypothesis that the observations come from the same population. Having concluded that a priori groups were significantly different, Altman then evaluated the classification accuracy of the model.

The model was tested using two alternative samples - the original 66 firm sample and a new 91 firm (25 bankrupt and 66 nonbankrupt) sample. The 25 new bankrupt firms represented an asset size range similar to that of the original sample. The 66 new nonbankrupt firms included manufacturing firms that suffered losses in either 1958 or 1961 (33 were randomly selected for each year). Altman felt that a sample of nonbankrupt firms that had encountered problems would provide a more rigorous test of the model. Table 2-5 presents the results of the classification tests. The original sample test results are followed by the new sample test result in parentheses. Note that Altman tested the new sample for one year prior to bankruptcy only.

Table 2-5
Altman Z-Score Model Classification Accuracy

	% Correct		
Years Prior To Bankruptcy	Bankrupt Sample	Nonbankrupt Sample	Total Sample
1	94(96)	97(79)	95
2	72	94	83
3	48		
4	29		
5	36		

These results led Altman to several observations. First, one financial statement (or year) prior to bankruptcy, the model classified 94 percent of the original bankrupt sample and 96 percent of the new bankrupt sample correctly. In the case of the original sample, this high success rate was expected since the firms are classified using a discriminant function which was based on the individual measurements of these same firms. In the case of the new sample, the even higher success rate was surprising, though promising.

Second, the model correctly classified 79 percent of the new nonbankrupt sample. This success rate was impressive given the fact that the firms in this sample were below-average performers. Third, and most important, model accuracy decreased the further a firm was from the bankruptcy event. According to Altman, the reduced accuracy made sense since impending bankruptcy was more remote and the indications were less clear. However, based on the above results, Altman concluded that the model was an accurate predictor of failure up to two years prior to bankruptcy.

In an attempt to extend the model for more general application, Altman determined a cutoff point to allow users to quickly make a bankrupt/nonbankrupt prediction. That is, all firms having a Z-score greater than 2.99 were classified nonbankrupt while those firms having a score below 1.81 were classified bankrupt. Since most of the misclassified firms had Z-scores that fell between 1.81 and 2.99, Altman defined this range as the zone of ignorance or grey area. When the Z-score of a firm falls between this range, a bankrupt/nonbankrupt prediction is less accurate.

2.2.3 Deakin (1972)

Deakin liked Beaver's empirical results for their predictive accuracy and Altman's multivariate approach because of its intuitive appeal. As such, the objective of this paper was to capture the best of both of these studies by performing discriminant analysis of 14 ratios studied by Beaver.[24]

Data Sample

Deakin selected 32 failed firms from a population that experienced failure between 1964 and 1970. For the purpose of this study, Deakin defined failure to include only those firms that experienced bankruptcy, insolvency, or were otherwise liquidated for the benefit of creditors.[25] Rather than using

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[24]Subsequent to the 1967 study discussed above, Beaver conducted a follow-up study that addressed a subset (i.e., 14) of the 30 ratios originally studied. See Beaver (1968). Deakin used this follow-up study as his starting point.

[25]This definition is narrower than Beaver's which includes firms that defaulted on loan obligations or missed preferred dividend payments.

a paired sample approach[26], Deakin randomly selected 32 nonfailed firms for the years 1962 to 1966. Deakin identified neither the number of different industries nor the asset size of the firms included in the database. All the financial information required to construct the 14 ratios was extracted from Moody's Industrial Manual.

Empirical Approach and Results

Deakin used discriminant analysis to determine the linear combination of the 14 ratios that had the greatest predictive accuracy. Based on much the same procedure employed by Altman (see Section 2.2.2), he found that the 14-variable set produced the most accurate classification results. When Deakin tried to reduce the number of variables the classification error increased significantly. The resulting 14-variable discriminant function was:

$$Z = 0.005X_1 + 0.083X_2 - 0.184X_3 - 0.101X_4 + 0.212X_5 - 0.176X_6 - 0.900X_7 + 0.052X_8 - 0.068X_9 + 0.096X_{10} - 0.020X_{11} - 0.074X_{12} + 0.069X_{13} + 0.209X_{14}$$

[26]That is, each failed firm is matched with a nonfailed firm on the basis of industry classification, year of the financial information provided and asset size.

where

X_1 = cash flow/total debt;
X_2 = net income/total assets;
X_3 = total debt/total assets;
X_4 = current assets/total assets;
X_5 = quick assets/total assets;
X_6 = working capital/total assets;
X_7 = cash/total assets;
X_8 = current assets/current liabilities;
X_9 = quick assets/current liabilities;
X_{10} = cash/current liabilities;
X_{11} = current assets/sales;
X_{12} = quick assets/sales;
X_{13} = working capital/sales;
X_{14} = cash/sales; and
Z = overall score.

Deakin tested the classification accuracy of this model using two alternative samples - the 64 firm sample upon which the model is based and a new 34 firm (i.e., 23 nonfailed and 11 failed) sample selected at random from the 1963 and 1964 editions of Moody's Industrial Manual. Table 2-6 summarizes the results of the classification tests. The original sample test results are followed by the new sample test results in parentheses.

These results led Deakin to several observations. First, in both the original and new sample test cases, the model's classification accuracy decreased significantly in the fourth and fifth years. Second, in the first year, the classification accuracy for the new sample was greatly reduced relative to the original sample. Deakin observed that,

Table 2-6
Deakin Model Classification Accuracy

	% Correct		
Years Prior To Bankruptcy	Failed Sample	Not Failed Sample	Total Sample
1	97(77)	97(82)	97.0(79.5)
2	94(96)	97(92)	95.5(94.0)
3	97(94)	94(82)	95.5(88.0)
4	75(91)	84(67)	79.5(79.0)
5	91(87)	75(78)	83.0(82.5)

although the new sample test results are expected to be less promising than those for the original sample, the first year reduction from 97 to 77 percent "cannot be explained by the presence of any unusual events peculiar to the sample used." Third, in the case of the failed firms, the model's accuracy for the new sample was either better or slightly worse than the original sample in four of the five years. The fact that the model classified the new sample better in two years was a surprising but promising finding. Based on the results above, Deakin concluded that this model can be used to predict business failure as far as three years in advance with fairly high accuracy.

2.2.4 Altman, Haldeman and Narayanan (1977)

The purpose of this study was to develop and test a new bankruptcy classification model, ZETA[27], based on a set of the most recent business failures. The developers of ZETA felt that existing models were founded on databases that no longer reflected the characteristics of current business failures (e.g., the size of failed firms had grown).

Data Sample

The model data sample comprised 53 bankrupt firms[28] and 58 nonbankrupt firms matched to the failed group by industry and year of data. The sample was almost equally divided into manufacturers and retailers and 50 of the 53 firms failed between 1969 and 1975. The average asset size of the bankrupt firms two annual reporting periods prior to failure was approximately $100 million; none of these publicly held firms

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[27]The ZETA model is trademarked as it was developed jointly with a private financial firm (Wood, Struthers & Winthrop) and is now marketed by ZETA Services, Inc.

[28]All but five of these firms filed bankruptcy petitions. Five non-filing firms were included as bankrupt due to either substantial government support (one firm), a forced merger (one), or bank take-over (three).

had less than $20 million in assets.[29]

Five years worth of financial data were collected for each of the 111 firms.[30] These data were used to compute 27 financial ratios (i.e., variables) that were considered for inclusion in the model.

Empirical Approach and Results

Altman et al. used discriminant analysis to derive the model with the greatest classification accuracy. Based on essentially the same procedure employed by Altman in developing the Z-score model (see Section 2.2.2), the authors found that the most accurate model included seven of the 27 financial ratios evaluated. The seven variables were:

X_1 = earnings before interest and taxes/total assets;
X_2 = standard error of the estimate around a ten-year trend in X_1 (normalized);
X_3 = earnings before interest and taxes/total interest payments;
X_4 = retained earnings/total assets;
X_5 = current assets/current liabilities;
X_6 = common equity/total capital; and
X_7 = total assets.

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[29]This is in contrast to Altman's Z-score model where the largest firm had assets of less than $25 million.

[30]The authors do not cite the data sources but it is probably fair to assume that one of the sources was Moody's Industrial Manual.

Unfortunately, due to the fact that the ZETA model is trademarked and marketed as a service, the coefficients associated with these variables have not been published.

Altman et al. conducted two tests of the ZETA model's classification accuracy. First, similar to Altman's evaluation of his Z-score model, the authors used: 1) the one year prior to bankruptcy data underlying the model to test model accuracy in that year and 2) the two-to-five years prior to failure data, or "holdout" data, to test model accuracy in those years. These results are shown in Table 2-7. Based on one year prior data,

Table 2-7
ZETA Model Classification Accuracy

	% Correct		
Years Prior To Bankruptcy	Bankrupt Sample	Nonbankrupt Sample	Total Sample
1	96.2	89.7	92.8
2	84.9	93.1	89.0
3	74.5	91.4	83.5
4	68.1	89.5	79.8
5	69.8	82.1	76.8

the model correctly classified 96 and 90 percent of the bankrupt and nonbankrupt firms, respectively. As expected, the model's classification accuracy deteriorated as the time prior to bankruptcy increased. However, the authors observed that 70 percent accuracy as early as five years prior to failure "compares favorably" to Altman's Z-score model results, where the accuracy fell significantly after the second year.

Second, Altman et al. constructed a test procedure that involved randomly selecting one-half of the original sample, reestimating the model coefficients with this half and testing the reestimated model's accuracy with the other half of the original (or holdout) sample. Table 2-8 depicts the results of this test, which was performed twice. The authors observed that model accuracy is "still quite impressive for

Table 2-8
Reestimated ZETA Model Classification Accuracy

	% Correct			
	Replication 1		Replication 2	
Year	Bankrupt Sample	Nonbankrupt Sample	Bankrupt Sample	Nonbankrupt Sample
1	92.5	91.4	96.2	79.6
2	84.9	91.4	86.8	81.0
3	76.5	91.4	80.4	79.3
4	61.7	93.0	74.5	82.5
5	62.8	84.0	69.8	76.8

independent observations."

In addition to testing the ZETA model's classification accuracy, Altman et al. compared the ZETA and Z-score models in several ways. First, and most straightforward, the five year classification accuracy of the models was compared (see Section 2.2.5). Next, the five year classification accuracy of ZETA was compared to the five year accuracy of the Z-score model applied to the 111 firm ZETA data sample. That is, the authors input data for each of the 111 ZETA firms into the Z-score model (see Section 2.2.2), computed Z-scores for each firm and classified them as bankrupt if Z < 1.81 and nonbankrupt if Z > 2.99. Then the classification accuracy of applying the new sample to the "old" model was computed. This test, which is identical in purpose and design to the test performed in this thesis (see Section 3.2), produced the results shown in Table 2-9. These results indicate that in

Table 2-9
ZETA vs. Z-Score Model Classification Accuracy

	% Correct			
	ZETA Model		Z-Score Model (ZETA Sample)	
Year	Bankrupt Sample	Nonbankrupt Sample	Bankrupt Sample	Nonbankrupt Sample
1	96.2	89.7	86.8	82.4
2	84.9	93.1	83.0	86.2
3	74.5	91.4	70.6	91.4
4	68.1	89.5	61.7	86.0
5	69.8	82.1	55.8	86.2

every year (with the exception of year five for the nonbankrupts) the ZETA model dominated the Z-score model applied to the ZETA data sample.

Altman et al. concluded that the strength of the model should be measured not only by its apparent classification accuracy but also by its underlying database which was representative of the most current (i.e., 1977) bankruptcy conditions.

2.2.5 Comparison of Model Classification Accuracy

As a means of summarizing the model results presented above, this section compares the classification accuracy of the four models.[31] Table 2-10 compares model accuracy for bankrupt (or, in Beaver's model, failed) firms. The first value is the accuracy (i.e., percent correctly classified) of the model with respect to the original sample. The value in parenthesis is the model's accuracy with respect to either a subset of the original sample (for Beaver and Altman et al.) or a new sample (for Altman and Deakin). These results indicate that, for all models and all test samples, classification accuracy declined (albeit at varying rates) the

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[31]It should be noted that the Beaver model is univariate and the other three models are multivariate.

Table 2-10*
Comparison of Bankruptcy Classification Accuracy for Four Models

Years Prior To Bankruptcy	% Correct Beaver (1967)	Altman (1968)	Deakin (1972)	Altman et al. (1977)
1	90(87)	94(96)	97(77)	96(93)(96)
2	82(79)	72	94(96)	85(85)(87)
3	79(77)	48	97(94)	75(77)(80)
4	76(76)	29	75(91)	68(62)(75)
5	78(78)	36	91(87)	70(63)(70)
Sample Size	79	33(25)	32(11)	53(26)(26)

* Blanks indicate that either the value was not published or the value was not computed.

further a firm was from bankruptcy. However, it is difficult to tell which model discriminated best. Different data and different procedures underlie the test results of the four models. Nevertheless, the accuracy percentages depicted in Table 2-10 suggest that the best multivariate model discriminated better than the best univariate model, but that the best univariate model outperformed some of the multivariate models.[32]

[32]See Scott (1981) for a further comparison of these and other models.

CHAPTER 3

DOD HARDWARE CONTRACTOR Z-SCORE MODEL

This first section of this chapter describes Dagel and Pepper's model for predicting Department of Defense (DOD) hardware contractor financial distress.[33] As explained in Chapter 1, the Department of the Navy (DON) has used the model since late 1988 for a variety of purposes. The second section of this chapter describes the evaluation of the model performed for this thesis.

3.1 Model Description

This chapter describes the DOD Z-score model (DODZSM), including its underlying database, variables and classification accuracy.

3.1.1 Data Sample

The data sample comprised 29 bankrupt and 29 nonbankrupt firms. All 58 firms were publicly held corporations traded on the New York Stock Exchange (NYSE) or the Over-the-Counter (OTC) market. The authors compiled a sample of companies that

[33]See Dagel and Pepper (1990). Hereafter, this model is referred to as the DOD Z-score model (DODZSM).

was as representative as possible of DOD hardware contractors. Since research[34] had shown that the significance of accounting ratios varied from one industry to the next, it was important to limit the database to manufacturing firms. Specifically, the authors included firms in the defense industry and other manufacturing firms that were comparable in nature to defense firms.

As was true for all the models described in Chapter 2, the authors selected the sample of bankrupt firms first. The selection criteria required that each bankrupt firm: 1) derived its primary source of income from manufacturing and 2) filed a bankruptcy petition under Chapter 11 of the Bankruptcy Reform Act of 1978 during the period 1982 to 1986. A list of 72 firms that filed during this period was provided in the 1987 Securities and Exchange Commission's (SEC) annual report. Twenty-nine of these firms, including defense and non-defense concerns[35], met the criteria above and were included in the bankrupt sample. Approximately one-third of these firms derived a portion of their income from DOD hardware contracts.

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[34]See Lincoln (1984)

[35]Unfortunately, it was impossible for the authors to compile a database of bankrupt DOD firms since, for one reason or another, so few have filed for bankruptcy. In order to achieve a sufficient sample size, non-defense firms had to be included in the sample.

The mean asset size of the 29 bankrupt firms was $440 million, with a range of $2 million to $6.3 billion.

An equal size sample of nonbankrupt firms was selected for the same time period as the bankrupt firms. In order to make the two samples as comparable as possible, the authors selected 10 of the 29 nonbankrupt firms from a list of the major United States defense contractors. The remaining 19 were manufacturing firms chosen at random from Moody's Industrial Manual and Moody's OTC Manual. The mean asset size of the 29 nonbankrupt firms was $2.5 billion with a range of $3 million to $26 billion.

Financial line item data were compiled for each of the 58 firms. With regard to bankrupt firms, data were collected from financial statements for each of the five annual accounting periods preceding the Chapter 11 filing. In the case of nonbankrupt firms, data were gathered from financial statements for one year chosen randomly between 1982 and 1986.[36]Although several years of data were collected for each firm, it is important to note that DODZSM was based on one year of data per firm, including the year prior to bankruptcy

[36]See Appendix D of Dagel and Pepper (1990) for a list of the 58 firms and their respective asset size, year of Chapter 11 filing (for bankrupt firms) and randomly selected year (for nonbankrupt firms).

for bankrupt firms and the randomly selected year for nonbankrupt firms. The remaining four years of data for each bankrupt firm were used to test the predictive power of the model.

For each firm, 15 financial line items were collected and used to compute 18 financial ratios that were variables in earlier bankruptcy prediction models. These ratios (i.e., variables) were organized into four general categories: liquidity, debt, profitability and activity ratios.[37] In addition to the 18 ratios, one of the 15 line items (i.e., total assets) was also considered for inclusion as a variable in the model.

3.1.2 Empirical Approach and Results

The authors used multivariate discriminant analysis as the statistical procedure for determining the best combination of the 19 variables being considered.[38] The

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[37]Page 10 of Dagel and Pepper (1990) identifies the 18 financial ratios.

[38]To be precise, it should be noted that Dagel and Pepper made the point that selection of the six model variables was accomplished by stepwise discriminant analysis together with procedures such as evaluation of correlation, t-test and F-test statistics, classification accuracy evaluation and analyst judgement based on financial theory. See Dagel and Pepper (pp. 16-17).

resulting linear model, or DODZSM, was:

$$Z = 1.54 - 6.48X_1 + 4.61X_2 - 0.41X_3 + 9.31X_4 - 5.40X_5 + 1.63X_6$$

where

X_1 = total debt/total assets;
X_2 = cash flow/total debt;
X_3 = current assets/current liabilities;
X_4 = quick assets/total assets;
X_5 = working capital/total assets; and
X_6 = net sales/total assets.

For an observation on any given firm, the firm was classified as nonbankrupt if $Z > 0$ and bankrupt if $Z < 0$.

The authors evaluated the classification accuracy of DODZSM. First, the model was used to develop Z-scores for each of the 58 firms upon which the model was based. In the case of bankrupt firms, this means that a Z-score was computed for the year prior to bankruptcy. For the nonbankrupt firms, this means that a Z-score was computed for the year that was selected randomly between 1982 and 1986. Second, the model was used to develop Z-scores for each of the 29 bankrupt firms for the four years (i.e., years two-to-five) prior to bankruptcy not used to develop the model. Table 3-1 presents these classification results.

Table 3-1
DODZSM Classification Accuracy

Years Prior To Bankruptcy	% Correct Bankrupt Sample	% Correct Nonbankrupt Sample	% Correct Total Sample
1	97	97	97
2	64		
3	60		
4	44		
5	24		

The results of the first test indicated that the model correctly classified 28 of the 29 (97 percent) bankrupt and nonbankrupt firms included in the original (i.e., model) sample. That is, only one bankrupt firm was misclassified as nonbankrupt and vice versa. These results compare favorably to similar test results for the financial distress models described in Chapter 2 (see Table 2-10).

The results of the second test demonstrated that the rate of successful classification declined the further a firm was from bankruptcy. This result, which parallels the outcomes of other financial distress models[39], was expected since: 1) indications of financial hardship are typically less obvious

[39]However, it should be noted that the rate of classification accuracy decay exhibited by DODZSM is greater than that for other financial distress models (see Table 2-10). The reason for this result is unclear.

the further a firm is from bankruptcy and 2) the year two-to-five data was not used to develop DODZSM. The overall results for years two-to-five compare favorably to Altman's Z-score model, but are not as good as the other three models addressed in Chapter 2. Based on the results of both tests, the authors concluded that DODZSM "does appear to be a reliable indicator of financial distress for up to three years prior to bankruptcy."

Subsequent to testing DODZSM's classification accuracy, Dagel and Pepper used the Z-scores for the 58 firms to compute the mean Z-scores shown in Table 3-2. The authors'

Table 3-2
DODZSM Mean Z-Scores

Years Prior To Bankruptcy	Bankrupt Sample	Nonbankrupt Sample
1	-2.45	2.45
2	-0.13	
3	0.21	
4	0.66	
5	1.44	

observations regarding these means were as follows. First, the bankrupt means demonstrated a decreasing trend as the firms approach bankruptcy. Second, although the fifth year prior was positive and therefore classified nonbankrupt, it was well below the nonbankrupt mean. Third, between two and three years prior to bankruptcy, the mean Z-score crossed the nonbankrupt/bankrupt cutoff point (i.e., zero). This means that the average bankrupt firm was classified as bankrupt two accounting periods (i.e., years) prior to bankruptcy.

Based on these observations, the authors concluded that the "trend in mean values represents one sign of stability of the model." Furthermore, they recommended that the model be used to evaluate a firm over time and that the resulting Z-scores be compared to the mean trend shown in Table 3-2.

Next, Dagel and Pepper validated DODZSM with a method known as Lachenbruch's holdout procedure.[40] Basically, the procedure holds out one observation (of 58 total) at a time, estimates a discriminant function (based on the other 57) and then uses the discriminant function to classify (i.e., compute a Z-score for) the holdout observation. Using this procedure, 28 of 29 nonbankrupt firms and 26 of 29 bankrupt firms were correctly classified for an overall 93 percent correct classification. Because this procedure represented a more rigorous test than simply plugging the original sample into

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[40]See Lachenbruch and Mickey (1968) for the development of this procedure and Morrison (1976) for evidence on the performance of this procedure.

the model,[41] the authors concluded that the Lachenbruch test results indicate that the DODZSM "should perform reliably in future applications."

Dagel and Pepper also tested DODZSM's accuracy by computing Z-scores for a sample of ten major nonbankrupt DOD hardware contractors not included in the original nonbankrupt sample. These Z-scores (all for 1987) are shown in Table 3-3. Only one of the nonbankrupt contractors

Table 3-3
1987 Z-Scores for Ten Major DOD Contractors

Firm	Z-Score
A	3.58
B	3.17
C	3.03
D	2.41
E	2.35
F	1.75
G	1.31
H	0.63
I	0.33
J	-0.10

(i.e., firm J) was misclassified as bankrupt. In this case, however, other information available to the authors indicated that the firm "may be in serious financial problems" due to

[41]Those test results, which indicated an overall classification accuracy of 97 percent, were previously displayed in Table 3-1.

cash flow difficulties and rising debt ratios. Furthermore, the three top and the remaining bottom scoring firms were evaluated for reasonableness. The authors found that both the strong and weak appearing firms had good reasons for their respective scores.

Similar to Altman's idea of a grey area[42], Dagel and Pepper attempted to extend the model for more general application. The aforementioned classification test results and mean Z-scores suggested that, in addition to a straightforward bankrupt or nonbankrupt (i.e., black or white) classification, a third classification - "weakly solvent"[43] - was appropriate and useful to model users.

To explain, the authors observed that: 1) the Z-score of the one (of 29) bankrupt firm misclassified as nonbankrupt was between zero and the nonbankrupt mean (2.45) and 2) the mean Z-scores for three, four and five years prior to bankruptcy were also between zero and the nonbankrupt mean. Dagel and Pepper believed that firms having Z-scores in this grey area

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[42]See p. 28 of this thesis and Altman (1968)

[43]In general textbook terms, a firm that is able to meet its current obligations is considered solvent. Though not explicitly defined by Dagel and Pepper, the term weakly solvent is meant to apply to firms that are on the verge of having difficulty doing so.

were "suspect" and should be classified as weakly solvent. They also felt that the firms classified as weakly solvent (i.e., 0 < Z < 2.45) and the firms classified as bankrupt (i.e., Z < 0) should be classified together as "potentially bankrupt." By expanding the classification rule, Dagel and Pepper sought to minimize the number of distressed firms that DODZSM misclassified as nonbankrupt.[44] This expanded classification scheme is illustrated in Figure 3.1, reproduced from the authors' journal article.

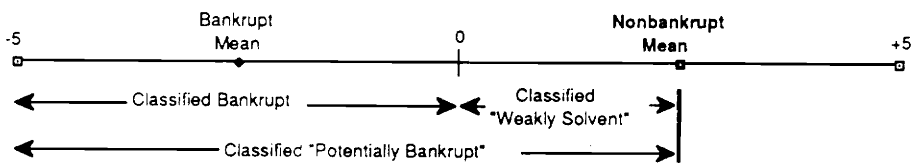

Figure 3.1 DODZSM Expanded Classification Scheme

Using this expanded classification scheme, the authors revisited the Z-scores previously computed for the 29 bankrupt

[44]See Chapter 4 for a discussion of the costs associated with misclassification, i.e., bankrupt firms misclassified as nonbankrupt (type I error) and vice versa (type II error).

firms and reclassified each firm. Table 3-4 presents the results of the expanded classification. The weakly solvent

Table 3-4
DODZSM Expanded Classification Accuracy

	% Correct		
Years Prior To Bankruptcy	Bankrupt	Weakly Solvent	Potentially Bankrupt
1	97	3	100
2	64	16	80
3	60	24	84
4	44	32	76
5	24	40	64

values and the resulting potentially bankrupt values demonstrate the benefit offered by the expanded classification scheme.[45] That is, the sum of the weakly solvent values, which increase steadily the further a firm is from bankruptcy, and the bankrupt values, which decrease steadily the further a firm is from bankruptcy, result in potentially bankrupt values that classify anywhere from three to forty percent more of the bankrupt firm sample correctly. Based on the potentially bankrupt results shown in Table 3-4, the authors concluded that DODZSM's expanded classification procedure "can thus give an indication of potential financial distress for up

[45]The benefit is less type I error. However, it should be noted that this benefit is typically at the cost of greater type II error. Dagel and Pepper did not address the type II error associated with the expanded classification scheme.

to five years prior to bankruptcy."[46]

3.2 Model Evaluation

This section details the evaluation of DODZSM for this thesis. The evaluation involved: 1) development of a new, more recent data sample[47] that comprises financial information for 72 firms not included in the original sample; 2) use of these data to compute the six financial ratios that represent DODZSM's variables; 3) application of DODZSM to compute Z-scores (i.e., a profile of) for each of the 72 firms; and 5) analysis of DODZSM's classification accuracy relative to the thesis data sample.

3.2.1 Firm Selection

The thesis data sample is composed of 36 bankrupt and 36 nonbankrupt firms that are public corporations traded on the New York Stock Exchange (NYSE) or the Over-the-Counter (OTC)

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[46]This conclusion is in contrast to the authors' earlier and narrower conclusion (see p. 41) that (based solely on the percent of the bankrupt firm sample correctly classified as bankrupt) the model "does appear to be a reliable indicator of financial distress for up to three years prior to bankruptcy."

[47]Hereafter referred to as the thesis data sample. This is in contrast to the original data sample, which Dagel and Pepper used to develop DODZSM.

market. The data sample was constructed using similar ground rules applied to the original data sample.

The bankrupt firms were selected first based on the following criteria: 1) each firm derived its primary source of income from manufacturing characterized by processes and materials applicable to the defense industry and 2) each firm filed a bankruptcy petition under Chapter 11 of the Bankruptcy Reform Act of 1978 sometime between first quarter fiscal year 1987 (FY 87) and third quarter FY 91[48]; and 3) financial data availability.

In order to ensure that the first criterion was satisfied, only firms having appropriate standard industrial classification (SIC) codes were chosen.[49] With regard to the second criterion, an SEC listing of 512 firms filing Chapter 11 petitions during the noted period was obtained from the

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[48]That is, U.S. Government fiscal year, or October 1 through September 30 of the following year. It should be noted that DODZSM's original data sample covers calendar years 1982 to 1986. This means that the thesis data sample includes more recent data but overlaps the original sample by one quarter (i.e., first quarter FY 87, which is October through December 1986).

[49]That is, SICs 3300 through 3700 plus SIC 3812. Appendix A identifies these codes. Although SICs 3700 and 3812 are directly related to defense manufacturing, the criterion needed to be expanded beyond these SICs in order to compile a reasonable size bankrupt sample.

SEC's public reference room. In relation to the third criterion, several data sources were investigated. These sources are described in Section 3.2.2. Of the possible 512 bankrupt firms, only 36 met the criteria above.

Table 3-5 identifies these firms, the fiscal year each filed for bankruptcy and the size of each firm expressed in total assets two annual accounting periods prior to filing for bankruptcy. Two characteristics of the sample should be noted. First, the mean asset size of the 36 bankrupt firms is $187 million, with a range of $1 million to $1.6 billion. Thus, the thesis sample mean asset size is less than half of the original sample mean.[50] Second, one-third (12) of the 36 firms derived either some or most of their income from direct and indirect sales to DOD.[51] This is coincidentally the same ratio reflected in the original data sample.

An equal size and similar composition sample of

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[50]In contrast, the mean asset size of the 29 bankrupt firms in the original sample is $440 million and the range is $2 million to $6.3 billion. However, since Dagel and Pepper evaluated total assets as a variable and found it was insignificant based on univariate t-test and multivariate f-test results, this difference should not matter.

[51]That is, directly as a prime contractor and indirectly as either a subcontractor to a prime or a subcontractor to another subcontractor.

TABLE 3-5
FIRMS INCLUDED IN THESIS DATA SAMPLE
(MILLIONS OF $)

BANKRUPT FIRMS	FY CH 11 FILED	TOTAL ASSETS **	NONBANKRUPT FIRMS	TOTAL ASSETS***
ALLEGHENY INTERNATIONAL CORP	88	1,200	ALPHA MICROSYSTEMS	28
ALLIS CHALMERS CORP	87	675	ANDAL CORP	68
AMDURA CORP	89	210	ARROW AUTOMOTIVE INDUSTRIES	62
BARTON INDUSTRIES	90	17	AUGUT INC	273
BASIX CORP	88	230	BUNTING INC	3
BELL PETROLEUM SERVICES INC	87	21	COMPUTER NETWORK TECHNOLOGY CORP	13
BICOASTAL CORP *	89	1,589	COMPUTER SCIENCES CORP *	918
CANTON INDUSTRIAL CORP	88	3	CONTROL DATA CORP *	1,424
CF&I STEEL CORP	90	269	CRESTEK INC	9
CHYRON CORP	90	70	DANAHER CORP	745
COMBUSTION PROTECTION CORP	87	4	DYNASCAN CORP	95
DEST CORP	89	28	ELEXIS CORP	6
DIGITAL TRANSMISSION INC	89	11	FRANKLIN ELECTRONIC PUBLISHING	27
EAGLE PICHER *	91	479	FRANKLIN TELECOMMUNICATIONS	3
ECONO-THERM ENERGY SYSTEMS CORP	87	23	GENERAL DYNAMICS CORP *	5,736
E-H INTERNATIONAL INC *	89	1	HARNISCHFEGER INDUSTRIES INC	1,576
ENGINEERED SYS & DEVELOP CORP *	88	20	HASTINGS MANUFACTURING CO	44
EQUINOX SOLAR INC	88	4	IIS INTELLIGENT INFORMATION CO	38
GF CORP	89	73	MEDALIST INDUSTRIES	82
HELIONETICS INC *	87	44	MICROPOLIS CORP	217
KAISER STEEL CORP *	87	711	MOTOROLA INC *	8,742
KENAI CORP	87	108	PALABORA MINING	403
KEYSTONE CAMERA PRODUCTS CORP	89	48	PENN CENTRAL CORP *	1,947
LAPOINTE INDUSTRIES *	89	6	PICTURETEL CORP	28
MARGAUX CONTROLS INC	89	20	POLK AUDIO INC	15
NBI INC	91	85	PROFIT TECHNOLOGY INC	13
OVERMYER CORP	90	25	RAYTHEON CO *	6,310
PENGO INDUSTRIES	88	62	RECOTON CORP	30
PRIAM CORP *	90	90	REDLAW INDUSTRIES INC	59
RAMTEK CORP *	88	33	TELEBYTE TECHNOLOGY INC	3
SCAT HOVERCRAFT INC	89	3	TENNECO INC *	13,096
SIGMA RESEARCH INC *	87	6	TEXAS INSTRUMENTS INC *	5,004
TODD SHIPYARDS INC *	88	497	TEXTRON INC *	4,289
TVI CORP *	89	6	TRW INC *	5,555
UNA CORP	88	23	UNISYS CORP *	9,239
ZIMMER CORP	88	35	WESTINGHOUSE ELECTRIC CORP *	10,343
	MEAN	146	MEAN	2,123

* = DOD FIRM
** = TWO ACCOUNTING PERIODS (I.E., YEARS) PRIOR TO YEAR IN WHICH CHAPTER 11 PETITION FILED
*** = 1990 ACCOUNTING PERIOD

nonbankrupt firms was selected randomly for this thesis. Shown in Table 3-5 also, the nonbankrupt sample includes 36 firms, 12 of which generate DOD sales. The non-DOD firms reflect not only the SIC codes shown in Appendix A but also approximately the same total asset value profile exhibited by the bankrupt non-DOD sample.[52] Similar to the original sample, the DOD firms were selected randomly from a list of the top 100 defense contractors (as measured by the value of FY 90 contract awards by DOD). This list is presented in Appendix B. The mean asset size of the nonbankrupt sample is $2.1 billion, with a range of $3 million to $13.1 billion. This mean is 16 percent less than that for the original data sample.[53]

3.2.2 Financial Data and Sources

Financial data were collected from a variety of sources for each of the 72 firms. These data included annual values for the eight balance sheet and two income statement line items used to compute the six financial ratios that represent

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[52]That is, if the bankrupt, non-DOD sample had two firms whose assets were between $1 million and $10 million, then two similar size nonbankrupt firms were randomly selected.

[53]The mean asset size of the 29 firms in the nonbankrupt sample underlying the DOD Z-score model is $2.5 billion. This represents a range of $3 million to $26 billion.

the DOD Z-score model's variables. The ten items are shown below:

- o balance sheet
  - cash
  - marketable securities
  - receivables
  - current assets
  - total assets
  - current liabilities
  - preferred stock
  - shareholder's equity
- o income statement
  - net sales
  - income before depreciation and amortization

Depending on the firm, these data were collected for a specific profile of years, or annual accounting periods, similar to the approach employed by Dagel and Pepper in developing DODZSM. In the case of bankrupt firms, data were compiled for the five years preceding the year in which the firm filed its Chapter 11 petition. For example, the data associated with a 1988 filing covers 1983 to 1987.[54] With regard to nonbankrupt firms, data were collected for a four

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[54]Given that the bankrupt sample includes firms that filed Chapter 11 petitions between October 1986 and June 1991, this means that data were collected for as far back as 1981 and as recent as 1990. In contrast, the original bankrupt sample included firms that filed between January 1982 and December 1986. This resulted in Dagel and Pepper collecting data covering the period 1977 to 1985.

year period (1987 to 1990).

As a rule, these data were extracted from the most centralized, readily available and easy-to-use sources. The primary sources of bankrupt firm data were Moody's Industrial Manual and Moody's Over-the-Counter Manual, which are reference documents updated annually. In those instances where Moody's was not sufficient, microfiche of company annual reports and SEC Form 10Ks were consulted. The source of nonbankrupt firm data depended on the type of firm. For non-DOD firms, the data source was COMPUSTAT, an automated financial database service to which my employer[55] subscribes. For DOD firms, the data source was a report published by my employer that includes data provided by company annual reports, SEC Form 10Ks and 10Qs and company officials.[56]

3.2.3 Empirical Approach and Results

Having collected the appropriate financial data, the next

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[55]The author is employed by the Naval Center for Cost Analysis (NCA), a field agency of the Comptroller of the Navy which performs Navy weapon system cost estimation, Navy contract performance measurement and Navy contractor financial health analysis.

[56]This is a business sensitive report not available outside the DOD. See Blackburn et al. (1991) in the list of references.

major step of this thesis involved employing DODZSM to derive Z-scores for each firm and year in the thesis data sample. This was accomplished through the use of a LOTUS 1-2-3 spreadsheet designed by Dagel and Pepper. Presented as Table 3-6, this spreadsheet requires the user to input values for the balance sheet and income statement items identified in the previous section. Based on these inputs and an intermediate calculation, the spreadsheet computes the six financial ratios that constitute DODZSM's variables and then uses these and DODZSM's coefficients to derive the annual Z-scores for each firm.

Tables 3-7 and 3-8 present the Z-scores computed for the thesis data sample bankrupt and nonbankrupt firms, respectively. As discussed earlier, five years worth of Z-scores are shown for each bankrupt company[57], beginning with the year prior to filing the bankruptcy petition and extending backward in time four years. Four years (1987 to 1990) of Z-scores are presented for each nonbankrupt firm. Additionally, one of the same four years' Z-scores was randomly selected for each nonbankrupt firm. Recall from Section 3.1.1 that the DODZSM was based on only one year of data per firm, including

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[57]To be precise, there were actually 33 companies for which five years of data were available. The other companies had been in existence less than five years when they filed Chapter 11 petitions.

TABLE 3-6
DODZSM SPREADSHEET

ALLEGHENY INTERNATIONAL INC.

BALANCE SHEET DATA

	9/27/87	12/28/86	12/29/85	12/30/84	1/1/84
1) Cash	$22,372,000	$31,618,000	$25,675,000	$59,364,000	$78,640,000
2) Marketable Securities	$0	$0	$0	$0	$0
3) Receivables	$212,777,000	$286,153,000	$287,253,000	$370,484,000	$350,011,000
4) Current Assets	$524,365,000	$729,609,000	$716,186,000	$886,461,000	$909,868,000
5) Total Assets	$850,488,000	$1,182,974,000	$1,309,990,000	$1,694,956,000	$1,856,170,000
6) Current Liabilities	$429,033,000	$496,813,000	$414,269,000	$571,163,000	$602,418,000
7) Preferred Stock	$232,912,000	$231,022,000	$228,520,000	$295,607,000	$331,898,000
8) Shareholder's Equity	($27,983,000)	$207,196,000	$314,368,000	$537,763,000	$653,598,000

INCOME STATEMENT DATA

	9/27/87	12/28/86	12/29/85	12/30/84	1/1/84
9) Net Sales	$650,826,000	$1,327,063,000	$1,445,394,000	$1,510,717,000	$2,086,516,000
10) Income Before Depr & Amort	($267,931,000)	($129,773,000)	($71,854,000)	$52,959,000	$84,907,000

FINANCIAL LINE ITEMS USED IN RATIOS

	9/27/87	12/28/86	12/29/85	12/30/84	1/1/84
Total Debt	$1,111,383,000	$1,206,800,000	$1,224,142,000	$1,452,800,000	$1,534,470,000
Total Assets	$850,488,000	$1,182,974,000	$1,309,990,000	$1,694,956,000	$1,856,170,000
Cash Flow	($267,931,000)	($129,773,000)	($71,854,000)	$52,959,000	$113,271,000
Current Assets	$524,365,000	$729,609,000	$716,186,000	$886,461,000	$909,868,000
Current Liabilities	$429,033,000	$496,813,000	$414,269,000	$571,163,000	$602,418,000
Quick Assets	$235,149,000	$317,771,000	$312,928,000	$429,848,000	$428,651,000
Working Capital	$95,332,000	$232,796,000	$301,917,000	$315,298,000	$307,450,000
Net Sales	$650,826,000	$1,327,063,000	$1,445,394,000	$1,510,717,000	$2,086,516,000

FINANCIAL RATIOS IN MODEL

	9/27/87	12/28/86	12/29/85	12/30/84	1/1/84
Total Debt / Total Assets	1.30676	1.02014	0.93447	0.85713	0.82669
Cash Flow / Total Debt	−0.24108	−0.10753	−0.05870	0.03645	0.07382
Current Assets / Current Liab	1.22220	1.46858	1.72879	1.55203	1.51036
Quick Assets / Total Assets	0.27649	0.26862	0.23888	0.25360	0.23093
Working Capital / Total Assets	0.11209	0.19679	0.23047	0.18602	0.16564
Net Sales / Total Assets	0.76524	1.12180	1.10336	0.89130	1.12410
Z−SCORE *	−5.32	−2.90	−2.72	−1.87	−1.01

$$Z = 1.54 - 6.48X_1 + 4.61X_2 - 0.41X_3 + 9.31X_4 - 5.40X_5 + 1.63X_6$$

where

X_1 = total debt/total assets;
X_2 = cash flow/total debt;
X_3 = current assets/current liabilities;
X_4 = quick assets/total assets;
X_5 = working capital/total assets; and
X_6 = net sales/total assets.

TABLE 3–7
Z–SCORES FOR BANKRUPT FIRMS

	YEARS PRIOR TO CHAPTER 11 FILING				
	1	2	3	4	5
ALLEGHENY INTERNATIONAL CORP	−5.32	−2.90	−2.72	−1.67	−1.01
ALLIS CHALMERS CORP	−0.53	−2.74	−1.26	−1.32	−1.41
AMDURA CORP	−0.73	0.42	−2.69	−1.08	−1.46
BARTON INDUSTRIES	−4.59	−1.83	−1.65	−1.47	−3.23
BASIX CORP	−4.19	−3.47	−1.93	−1.04	−0.89
BELL PETROLEUM SERVICES INC	−0.74	−1.03	−1.99	0.98	1.87
BICOASTAL CORP *	1.34	1.20	1.41	1.87	1.71
CANTON INDUSTRIAL CORP	−4.92	−6.32	−10.56		
CF&I STEEL CORP	−1.18	−0.95	−0.25	−1.44	0.16
CHYRON CORP	1.42	−0.88	1.34	3.16	2.94
COMBUSTION PROTECTION CORP	0.01	4.24	2.74	2.72	
DEST CORP	−1.13	0.86	5.37	6.34	6.39
DIGITAL TRANSMISSION INC	−6.21	1.44	0.07	−0.50	−0.16
EAGLE PICHER *	−1.47	−3.66	−6.02	1.76	1.46
ECONO–THERM ENERGY SYSTEMS CORP	2.57	0.52	−0.22	1.91	0.58
E–H INTERNATIONAL INC *	−11.11	−12.46	−14.96	1.46	5.18
ENGINEERED SYS & DEVELOP CORP *	−1.2	−1.8	0.84	6.24	7.35
EQUINOX SOLAR INC	5.21	3.99	2.71	2.79	2.43
GF CORP	1.49	0.82	0.83	0.30	−2.63
HELIONETICS INC *	−2.09	−0.17	2.28	4.33	4.15
KAISER STEEL CORP *	−4.67	−3.54	−3.16	−4.25	−1.51
KENAI CORP	−5.05	−4.23	−3.87	−2.73	−0.27
KEYSTONE CAMERA PRODUCTS CORP	−1.65	−5.97	−1.63	−2.68	−2.88
LAPOINTE INDUSTRIES *	−1.63	−4.40	−2.78	2.32	1.02
MARGAUX CONTROLS INC	1.24	−3.97	−2.59	5.14	−4.16
NBI INC	−11.16	−5.47	−1.62	−2.00	1.39
OVERMYER CORP	1.00	0.21	−0.02	1.12	2.83
PENGO INDUSTRIES	−12.85	−9.80	−4.83	−8.88	−1.79
PRIAM CORP *	0.10	2.43	−0.36	3.21	−0.85
RAMTEK CORP *	−0.87	0.11	−0.87	−2.57	0.42
SCAT HOVERCRAFT INC	−1.74	−4.59	−4.53	−2.43	
SIGMA RESEARCH INC *	4.93	4.96	6.36	5.11	8.59
TODD SHIPYARDS INC *	0.53	−1.44	0.67	1.89	3.48
TVI CORP *	−3.56	−4.64	−2.62	0.94	0.97
UNA CORP	−1.24	−0.13	−0.30	−0.64	0.47
ZIMMER CORP	−1.72	−1.60	1.42	2.80	5.13
MEAN Z–SCORE	−1.99	−1.86	−1.32	0.62	1.10

* = DOD FIRM

NO Z–SCORE = FIRM EITHER DID NOT EXIST OR EXISTED FOR ONLY A PORTION OF THE ACCOUNTING PERIOD.

TABLE 3–8
Z–SCORES FOR NONBANKRUPT FIRMS

	1 Random***	2 1990	3 1989	4 1988	5 1987
ALPHA MICROSYSTEMS	6.80	2.58	4.77	7.56	6.80
ANDAL CORP	0.34	0.71	1.44	0.49	0.34
ARROW AUTOMOTIVE INDUSTRIES	−0.37	−0.49	0.58	−0.37	−0.63
AUGUT INC	3.29	3.41	3.29	0.91	2.00
BUNTING INC **	2.83	1.36	0.33	−0.49	2.83
COMPUTER NETWORK TECHNOLOGY CORP	5.02	4.38	5.02	0.41	−3.63
COMPUTER SCIENCES CORP *	5.02	5.20	5.86	5.46	5.02
CONTROL DATA CORP *	1.74	2.54	0.61	1.74	2.26
CRESTEK INC **	0.55	2.95	2.63	1.48	0.55
DANAHER CORP	0.49	0.49	1.94	0.03	−2.72
DYNASCAN CORP	2.02	−2.87	−2.26	0.47	2.02
ELEXIS CORP	−1.67	−5.97	−1.67	−3.55	−3.25
FRANKLIN ELECTRONIC PUBLISHING	−2.71	0.53	1.69	2.15	−2.71
FRANKLIN TELECOMMUNICATIONS	−0.78	2.47	−0.78	8.36	7.42
GENERAL DYNAMICS CORP *	4.62	2.89	3.33	3.81	4.62
HARNISCHFEGER INDUSTRIES INC	1.21	2.04	1.85	1.21	−0.27
HASTINGS MANUFACTURING CO	−0.30	0.28	−0.30	−0.26	−0.17
IIS INTELLIGENT INFORMATION CO **	8.17	7.56	9.90	8.17	9.79
MEDALIST INDUSTRIES	0.64	0.21	0.24	−0.26	0.64
MICROPOLIS CORP **	1.61	−1.16	−0.64	1.61	8.50
MOTOROLA INC *	2.83	2.72	2.83	3.03	3.03
PALABORA MINING **	2.91	2.91	0.69	0.03	−1.57
PENN CENTRAL CORP *	1.95	−1.35	−2.57	1.95	1.79
PICTURETEL CORP	−7.36	2.18	1.04	−2.58	−7.36
POLK AUDIO INC	4.75	4.84	6.62	4.75	7.52
PROFIT TECHNOLOGY INC	−1.09	−1.94	−7.78	−3.67	−1.09
RAYTHEON CO *	5.00	4.69	4.68	5.00	5.17
RECOTON CORP	−0.81	−0.23	−0.81	−0.86	−2.20
REDLAW INDUSTRIES INC **	2.23	0.05	2.23	2.70	2.73
TELEBYTE TECHNOLOGY INC	−1.14	−2.12	−1.14	−2.69	−0.74
TENNECO INC *	−0.41	−0.29	0.03	−0.41	−1.15
TEXAS INSTRUMENTS INC *	2.14	1.24	2.14	2.29	1.88
TEXTRON INC *	0.82	0.82	−0.61	−0.22	0.60
TRW INC *	2.08	2.08	2.06	2.37	2.33
UNISYS CORP *	0.59	−0.41	−1.06	−0.43	0.59
WESTINGHOUSE ELECTRIC CORP *	1.25	1.25	1.95	2.30	2.66
MEAN Z–SCORE	1.51	1.27	1.34	1.46	1.49

*   = DOD FIRM
** = 1990 DATA NOT AVAILABLE; PROFILE COVERS 1986 TO 1989
*** = RANDOM SELECTION FROM 1987–90 (OR 1986–89, WHERE APPLICABLE)

the year prior to bankruptcy for bankrupt firms and the randomly selected year for nonbankrupt firms.

The Z-scores presented in Tables 3-7 and 3-8 were used to evaluate DODZSM. First, classification accuracy was assessed. That is, how often did DODZSM successfully classify a bankrupt firm as bankrupt and a nonbankrupt firm as nonbankrupt?[58]

Table 3-9 compares DODZSM's classification accuracy for the thesis data sample and the original data sample. These results indicate that DODZSM, at best, correctly classified 71 percent of the total thesis sample.[59]

Table 3-9
DODZSM Classification Accuracy:
Thesis vs. Original Data Sample

% Correct

	Bankrupt		Nonbankrupt		Total	
Year	Thesis	Original	Thesis	Original	Thesis	Original
1	69	97	72	97	71	97
2	67	64	72		69	
3	67	60	69		68	
4	43	44	67		55	
5	39	24	64		52	

[58]Based on Dagel and Pepper's rule that a firm is classified as nonbankrupt if Z > 0 and bankrupt if Z < 0.

[59]That is, based on the results shown in Tables 3-7 and 3-8, the model correctly classified 25 of 36 (69 percent) bankrupt firms and 26 of 36 (72 percent) nonbankrupt firms. This equates to 51 of 72 (71 percent) firms in total.

This means that DODZSM misclassified more than one in every four firms total and nearly one in three bankrupt firms. This is in contrast to Dagel and Pepper's favorable (i.e., with respect to previous models) finding that 56 of 58 (97 percent) total firms in the original data sample were correctly classified.

Table 3-9 also presents DODZSM's classification accuracy for two-to-five years prior to bankruptcy. For these years, DODZSM's classification accuracy for the thesis sample is higher in all but one year relative to the original sample. Moreover, similar to Dagel and Pepper's (among others') findings, the results for the thesis data sample indicate that bankruptcy classification accuracy deteriorates the further a firm is from bankruptcy.

Next, the mean Z-scores were evaluated. Table 3-10 compares the mean Z-scores for the thesis sample (see Tables 3-7 and 3-8) with the mean Z-scores for the original sample. This comparison indicates that there is only one apparent similarity between DODZSM results for the thesis and original data samples. Specifically, for both bankrupt data samples, DODZSM yields a five-year Z-score profile that exhibits a decreasing trend as bankruptcy approaches. Otherwise, DODZSM produces different results for the two

Table 3-10
Mean Z-Scores: Thesis vs. Original Data Sample

	Bankrupt		Nonbankrupt	
Year	Thesis	Original	Thesis	Original
1	-1.99	-2.45	1.51	2.45
2	-1.86	-0.13		
3	-1.32	0.21		
4	0.62	0.66		
5	1.10	1.44		

bankrupt samples. Consider, for example, the absolute values and signs of the mean Z-scores. The absolute values of the Z-scores are significantly different in all but the fourth year (i.e., .62 vice .66). The signs of the Z-scores also differ; the Z-score profile for the thesis sample becomes negative one year earlier than the original sample. But, although the firms in the thesis sample seem to exhibit signs of bankruptcy earlier than those in the model sample, their mean Z-scores deteriorate less (i.e., -1.99 vice -2.45). Note that differences in DODZSM's results are not limited to the bankrupt samples. As displayed in Table 3-10, DODZSM also generates distinctly different mean Z-scores for the two nonbankrupt samples (i.e., 1.51 vice 2.45).

Based on these observations regarding the mean Z-scores, it is difficult to judge DODZSM's performance. However, two other points are worthwhile. First, the results for the thesis data sample indicate that DODZSM classified the average bankrupt firm as bankrupt (i.e., Z < 0) three years prior to bankruptcy. From the standpoint of the DODZSM's predictive ability, this is an appealing result. Second, the results for the thesis sample demonstrate that the mean Z-score for nonbankrupt firms was not much higher than the mean Z-score for bankrupt firms that were five years from bankruptcy. This finding is a bit unsettling since it implies that the average nonbankrupt firm was not much stronger financially than a firm that was within five years of bankruptcy.

Next, DODZSM was tested further using an alternative thesis data sample composed of nonbankrupt DOD hardware contractors only.[60] This sample includes 39 of the top 50 Navy contractors as measured by the value of FY 90 contract awards. As with the other nonbankrupt thesis sample shown in Table 3-8, data were collected for a four year period (1987 to 1990) and Z-scores were computed for each firm and year. Table 3-11 presents the Z-scores, including a column of randomly selected (with regard to year) Z-scores.

Based on these Z-scores, DODZSM's classification accuracy

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[60]Recall from Section 3.1.2 that Dagel and Pepper did the same for a sample of ten contractors. See Table 3-3 for these Z-scores.

TABLE 3-11
Z-SCORES FOR NONBANKRUPT DOD CONTRACTORS

	1 RANDOM **	2 1990	3 1989	4 1988	5 1987
ALLIED SIGNAL	0.61	0.34	0.61	0.46	0.33
AT&T	1.58	1.58	1.64	0.85	1.37
BOEING CO	2.84	4.81	2.84	3.61	3.02
COMPUTER SCIENCES CORP	5.02	5.20	5.86	5.46	5.02
CONTROL DATA CORP	2.26	2.54	0.61	1.74	2.26
CONTRACTOR A *	3.28	3.08	3.28	2.71	0.52
CONTRACTOR B *	−1.58	−0.27	−1.19	−1.58	−2.73
CONTRACTOR C *	0.69	0.35	0.69		
CONTRACTOR D *	4.28	3.40	2.79	3.89	4.28
EATON CORP	0.50	0.50	0.50	0.85	−0.27
EMERSON ELECTRIC CORP	2.56	2.97	2.56	2.38	2.04
FMC CORP	−0.26	−0.26	−0.46	−1.00	−1.51
GENERAL DYNAMICS CORP	2.89	2.89	3.33	3.81	4.62
GENERAL ELECTRIC CO	2.01	2.43	2.50	2.01	2.40
GM HUGHES ELECTRONICS	3.75	3.49	3.75	3.96	4.00
GRUMMAN CORP	−0.44	−0.44	−0.68	−0.07	−0.07
HONEYWELL INC	2.49	2.49	2.38	1.23	2.28
IBM CORP	2.68	2.68	2.59	2.68	3.45
ITT CORP	1.73	1.73	1.53	2.41	1.75
LITTON INDUSTRIES INC	0.33	0.26	0.17	0.20	0.33
LOCKHEED CORP	1.44	2.06	1.44	3.98	3.57
LORAL CORP	0.66	0.66	−1.00	−0.42	−1.73
MARTIN MARIETTA CORP	2.92	2.92	2.18	2.50	2.35
MCDONNELL DOUGLAS CORP	2.94	2.94	3.34	3.51	4.14
MORRISON KNUDSEN CORP	2.41	2.12	4.41	2.41	1.57
MOTOROLA INC	2.72	2.72	2.83	3.03	3.03
NORTHROP CORP	3.09	2.47	2.19	3.09	4.16
PENN CENTRAL CORP	1.79	−1.35	−2.57	1.95	1.79
RAYTHEON CO	4.68	4.69	4.68	5.00	5.17
ROCKWELL INTERNATIONAL CORP	3.05	2.65	3.05	2.93	3.27
TELEDYNE INC	−0.21	2.31	2.57	−0.21	2.91
TENNECO INC	−1.15	−0.29	0.03	−0.41	−1.15
TEXAS INSTRUMENTS INC	2.29	1.24	2.14	2.29	1.88
TEXTRON INC	0.60	0.82	−0.61	−0.22	0.60
THIOKOL CORP	2.36	1.12	0.24	2.36	2.98
TRW INC	2.37	2.08	2.06	2.37	2.33
UNISYS CORP	0.59	−0.41	−1.06	−0.43	0.59
UNITED TECHNOLOGIES CORP	0.84	0.89	1.17	0.84	0.54
WESTINGHOUSE ELECTRIC CORP	1.95	1.25	1.95	2.30	2.66
MEAN Z-SCORE	1.86	1.81	1.65	1.91	1.94

* = PRIVATELY-HELD CONTRACTOR WHOSE FINANCIAL INFORMATION IS COMPANY PROPRIETARY
** = RANDOM SELECTION FROM 1987-90
NO Z-SCORE = FINANCIAL DATA NOT AVAILABLE

was evaluated. Table 3-12 compares DODZSM's classification accuracy for this nonbankrupt sample (all DOD) and the other nonbankrupt sample (one-third DOD) addressed earlier. The

Table 3-12
DODZSM Classification Accuracy:
All DOD vs. One-Third DOD Thesis Data Sample

Year	% Correct All DOD	One-Third DOD*
1	87	72
2	85	72
3	82	69
4	79	67
5	85	64

* This is the same sample shown in Table 3-8 and classification results presented in Table 3-9.

results indicate that the model correctly classified a much higher percentage of the all DOD sample (i.e., 79 to 87 percent) than the mixed sample (i.e., 64 to 72 percent). While reasons for the model's improved performance are unclear, the outcome is appealing since the model was designed to analyze DOD contractors. It should also be noted that the mean Z-score for year one (random) of the all DOD sample (1.86) is 19 percent higher than that for the mixed sample (1.51).

As discussed in Section 3.1.3, Dagel and Pepper extended

DODZSM for more general application by adding a third classification - weakly solvent - to the bankrupt/nonbankrupt classification scheme. They defined a weakly solvent firm as one having a Z-score greater than zero but less than the nonbankrupt mean (i.e., $0 < Z < 2.45$). Moreover, they classified the combination of weakly solvent and bankrupt (i.e., $Z < 0$) firms as potentially bankrupt. Based on this expanded classification scheme, the bankrupt firm Z-scores computed for the thesis data sample (Table 3-7) and assessed for classification accuracy (Table 3-9) were reclassified.

Table 3-13 compares DODZSM's expanded classification accuracy for the thesis and original data samples. These

Table 3-13
DODZSM Expanded Classification Accuracy:
Thesis vs. Original Bankrupt Data Sample

% Correct

	Bankrupt		Weakly Solvent		Potentially Bankrupt	
Year	Thesis	Original	Thesis	Original	Thesis*	Original
1	69	97	22	3	92	100
2	67	64	25	16	92	80
3	67	60	22	24	89	84
4	43	44	29	32	71	76
5	39	24	33	40	73	64

* This column, the sum of the other two "thesis" columns, does not add due to rounding.

results indicate that DODZSM classified anywhere from 22 to 33 percent more of the thesis bankrupt firm sample correctly under the expanded vice the strict bankrupt (i.e., $Z < 0$) classification scheme. The outcome is that DODZSM correctly classified a high of 92 percent (in year one) and a low of 71 percent (in year four) of the thesis bankrupt firms as potentially bankrupt. Overall, the five-year potentially bankrupt profile shown in Table 3-13 for the thesis sample compares favorably with the profile for the original sample. Though the accuracy for year one is not as impressive (92 vice 100 percent), the accuracy increased significantly in years two (92 vice 80 percent) and five (73 vice 64 percent). Given these results, it is probably appropriate to conclude (as did Dagel and Pepper) that DODZSM "can give an indication of financial distress for up to five years prior to bankruptcy."

For reasons not explicitly stated, Dagel and Pepper did not apply the expanded classification scheme to the Z-scores computed for the original nonbankrupt data sample. In contrast and in the interest of completeness, this thesis does. When applied to nonbankrupt firm Z-scores, the weakly solvent classification rule necessarily overlaps with the nonbankrupt classification rule. That is, based on the classification rule for weakly solvent firms (i.e., $0 < Z < 2.45$), some of the nonbankrupt firms previously correctly classified as nonbankrupt (i.e., Z > 0) can be reclassified as weakly solvent and, therefore, potentially bankrupt. In order to assess the impact of these overlapping classification rules, the expanded classification scheme was applied to the nonbankrupt firm Z-scores computed previously for the thesis data sample (Table 3-8).

The results are displayed in Table 3-14, which compares the percentage of nonbankrupt firms correctly classified as

Table 3-14
Expanded DOD Z-Score Model Classification Accuracy: Nonbankrupt Thesis Data Sample

	% Correct		
Year	NonBankrupt	Weakly Solvent	Strongly Solvent
1	72	42	30
2	72	36	36
3	69	42	27
4	67	42	25
5	64	31	33

nonbankrupt and the overlapping percentage of nonbankrupt firms classified as weakly solvent. The results indicate that over half the nonbankrupt firms correctly classified as nonbankrupt were also classified as weakly solvent. As such, this means that the remaining nonbankrupt firms correctly classified as nonbankrupt (see the last column in Table 3-14) must represent the strongly solvent firms.

The implications of these findings are unclear, especially since Dagel and Pepper did not publish a comparable test for the model data sample. It is, however, surprising to observe that a majority of the nonbankrupt firms in the thesis sample are deemed weakly solvent and, therefore, potentially bankrupt. Perhaps the indication that the average nonbankrupt firm randomly selected for this thesis is a candidate for bankruptcy explains why the mean nonbankrupt Z-score for the thesis data sample (1.51) is much lower than that for the model data sample (2.45).

CHAPTER 4

CONCLUSIONS AND RECOMMENDATIONS

The goal of this thesis has been to evaluate the accuracy of the DOD Z-score model (DODZSM) employed by the Department of the Navy (DON). The model was tested with a sample of 72 bankrupt and nonbankrupt firms (i.e., 36 of each), none of which were included in the original sample used to develop the model.

Model accuracy was <u>computed</u> by measuring how often DODZSM correctly classified the bankrupt firms in the thesis sample as bankrupt and the nonbankrupt firms in the thesis sample as nonbankrupt. Model accuracy was <u>evaluated</u> by comparing these classification results to Dagel and Pepper's classification results for the original data sample. This approach (i.e., comparing model results for two different samples) was employed by previous bankruptcy model developers and produced mixed results.[61]

The results of my evaluation are likewise mixed. First, consider DODZSM's <u>classification accuracy for bankrupt firms</u>

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[61]That is, a given model's accuracy for the new data sample was sometimes better and sometimes worse than its accuracy for the original data sample. See the Altman (1968) and Deakin (1972) results in Table 2-10.

as depicted in Table 3-9. One year prior to bankruptcy, accuracy with respect to the thesis data sample is much less than with respect to the original data sample (69 vice 97 percent). Conversely, in years two-to-five prior to bankruptcy, accuracy for the thesis data sample is either equal to or better than for the original data sample.[62] Although the improved accuracy in years two-to-five is promising, the fact that DODZSM misclassified, at best, nearly one in three bankrupt firms leads me to conclude that the model is a poor indicator of bankruptcy.

Next, consider DODZSM's <u>classification accuracy for potentially bankrupt firms</u> as presented in Table 3-13. Dagel and Pepper constructed the potentially bankrupt (vice bankrupt) classification in order to extend DODZSM's applicability and, thereby, reduce the cost associated with

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[62]Recall from Section 2.2.4 and Table 2-9 that Altman et al. (1977) tested Altman's Z-score model (1968) with a new data sample characterized by a greater number of firms and a more recent timeframe than the original data sample (i.e., conducted the same type of test performed for this thesis). Interestingly, the results of that test were generally similar to the results of my test. That is, one year prior to bankruptcy, the Altman Z-score model's classification accuracy with respect to the new data sample (Table 2-5) was less than with respect to the original sample (Table 2-9). Conversely, in years two-to-five prior to bankruptcy, accuracy with respect to the new data sample was better than with respect to the original sample.

misclassification.[63] In two of the five years, DODZSM's accuracy with respect to the thesis data sample is less than with respect to the original data sample. In contrast, in the other three years, the model's accuracy for the thesis data sample is better than for the original data sample. Specifically, the model correctly classified 92 percent of the potentially bankrupt firms in the first and second years and 89 percent in the third year. Based on this finding and the fact that the fourth and fifth year accuracy is not less than 71 percent, it is fair to conclude that the model is a relatively good indicator of potential bankruptcy up to five years prior to bankruptcy.

Now consider DODZSM's <u>classification accuracy for a mix of nonbankrupt DOD and non-DOD firms</u> as shown in Table 3-9. DODZSM's classification accuracy with respect to the thesis

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[63]There are costs (to DOD) associated with either misclassifying a bankrupt firm as nonbankrupt or misclassifying a nonbankrupt firm as bankrupt. With respect to the former error, consider the case of a firm that wins a DOD contract but cannot deliver due to financial problems. The DOD will incur not only the sunk contract costs but also the costs associated with no product (e.g., schedule slippage, etc.). If this company had subtle problems, the narrowly-defined bankrupt classification rule (Z > 0) would misclassify the firm whereas the broadly-defined potentially bankrupt classification rule would classify correctly. Based on this indicator, the DOD could act accordingly (e.g., not award the contract to the firm in question). See Altman et al. (1977) and Trieschmann and Pinches (1972) for more on the concept of misclassification cost.

data sample is significantly less than with respect to the original sample. The fact that the model misclassified, on average, better than one in four nonbankrupt firms leads to the conclusion that DODZSM is a somewhat unreliable judge of nonbankruptcy. However, DODZSM's ability to predict nonbankruptcy is probably unimportant since: 1) the model is designed to indicate potential bankruptcy and 2) there is little cost associated with nonbankrupt firms being misclassified as bankrupt.[64]

Next, consider DODZSM's classification accuracy for nonbankrupt DOD contractors as displayed in Table 3-11. The model correctly classified from 79 to 85 percent of the thesis data sample (39 firms), a marked improvement over the results for the mixed nonbankrupt thesis sample. This is a positive finding in light of the fact that DODZSM was designed to analyze DOD contractors. In comparison, DODZSM correctly classified 90 percent of a ten contractor test sample (Table 3-3) compiled by Dagel and Pepper.

In addition to classification accuracy, my evaluation also considered the magnitude of the Z-scores generated by the

[64]The cost involves only the time that Navy analysts must spend to investigate determine whether the firm is really potentially bankrupt.

model. Mean Z-scores were computed for the thesis data sample (bankrupt and nonbankrupt) addressed above and compared to their original data sample counterpart. All but one mean Z-score computed for the thesis data sample are lower than the counterpart scores computed for the original sample by Dagel and Pepper. Recall that the thesis and original data samples differ with regard to mean asset size and time period.[65] Though further research is required, these sample differences may be a possible explanation for the disparity in mean Z-scores.[66] A possible test of the timeframe impact might be to compute industry-level mean Z-scores for different industries for the years in question and investigate for trends.

In conclusion, the foregoing mixed results indicate that DODZSM should be improved. I recommend that the original data sample (58 firms) be expanded to include the 72 firm sample compiled for this thesis and any other appropriate firms that have filed Chapter 11 petitions since July 1991. Based on

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[65]Mean asset size of thesis bankrupt firms is less than half that of original bankrupt firms and mean asset size of thesis nonbankrupt firms is 16 percent less than original nonbankrupt firms. The timeframes covered by the financial data (bankrupt and nonbankrupt) are 1981 to 1990 for the thesis and 1977 to 1986 for the model. See Sections 3.2.1 and 3.2.2 for more details.

[66]In light of Dagel and Pepper's finding that total assets was not a statistically significant variable, the difference in mean asset size probably will not explain the difference in mean Z-scores.

this expanded data sample, I recommend that multivariate discriminant analysis be used to test whether the six financial ratios employed by the model are still the most significant variables. Depending on the outcome of this analysis, I recommend that either: 1) the existing model's six coefficients be re-estimated or 2) a new model be developed.

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APPENDIX A
STANDARD INDUSTRIAL CLASSIFICATION (SIC) CODES

33 Primary Metal Industries

3312 Steel Works, Blast Furnaces (Including Coke Ovens) & Rolling Mills
3313 Electrometallurgical Products, Except Steel
3315 Steel Wiredrawing & Steel Nails & Spikes
3316 Cold-Rolled Steel Sheet, Strip & Bars
3317 Steel Pipe & Tubes
3321 Gray & Ductile Iron Foundries
3322 Malleable Iron Foundries
3324 Steel Investment Foundries
3325 Steel Foundries, NEC
3331 Primary Smelting & Refining of Copper
3334 Primary Production of Aluminum
3339 Primary Smelting & Refining of Nonferrous Metals, Except Copper & Aluminum
3341 Secondary Smelting & Refining of Nonferrous Metals
3351 Rolling, Drawing & Extruding of Copper
3353 Aluminum Sheet, Plate & Foil
3354 Aluminum Extruded Products
3355 Aluminum Rolling & Drawing, NEC
3356 Rolling, Drawing & Extruding of Nonferrous Metals, Except Copper & Aluminum
3357 Drawing & Insulating of Nonferrous Wire
3363 Aluminum Die-Castings
3364 Nonferrous Die-Castings, Except Aluminum
3365 Aluminum Foundries
3366 Copper Foundries
3369 Nonferrous Foundries, Except Aluminum & Copper
3398 Metal Heat Treating
3399 Primary Metal Products, NEC

34 Fabricated Metal Products, Except Machinery & Transportation Equipment

3411 Metal Cans
3412 Metal Shipping Barrels, Drums, Kegs & Pails
3421 Cutlery
3423 Hand & Edge Tools, Except Machine Tools & Handsaws
3425 Saw Blades & Handsaws
3429 Hardware, NEC
3431 Enameled Iron & Metal Sanitary Ware
3432 Plumbing Fixture Fittings & Trim
3433 Heating Equipment, Except Electric & Warm Air Furnaces
3441 Fabricated Structural Metal
3442 Metal Doors, Sash, Frames, Molding & Trim
3443 Fabricated Plate Work (Boiler Shops)
3444 Sheet Metal Work
3446 Architectural & Ornamental Metal Work
3448 Prefabricated Metal Buildings & Components
3449 Miscellaneous Structural Metal Work
3451 Screw Machine Products
3452 Bolts, Nuts, Screws, Rivets & Washers
3462 Iron & Steel Forgings
3463 Nonferrous Forgings
3465 Automotive Stampings
3466 Crowns & Closures
3469 Metal Stampings, NEC
3471 Electroplating, Plating, Polishing, Anodizing & Coloring
3479 Coating, Engraving & Allied Services, NEC
3482 Small Arms Ammunition
3483 Ammunition, Except for Small Arms
3484 Small Arms
3489 Ordnance & Accessories, NEC
3491 Industrial Valves
3492 Fluid Power Valves & Hose Fittings
3493 Steel Springs, Except Wire
3494 Valves & Pipe Fittings, NEC
3495 Wire Springs
3496 Miscellaneous Fabricated Wire Products
3497 Metal Foil & Leaf
3498 Fabricated Pipe & Pipe Fittings
3499 Fabricated Metal Products, NEC

35 Industrial & Commercial Machinery & Computer Equipment

3511 Steam, Gas & Hydraulic Turbines, & Turbine Generator Set Units
3519 Internal Combustion Engines, NEC
3523 Farm Machinery & Equipment
3524 Lawn & Garden Tractors & Home Lawn & Garden Equipment
3531 Construction Machinery & Equipment
3532 Mining Machinery & Equipment, Except Oil & Gas Field Machinery & Equipment
3533 Oil & Gas Field Machinery & Equipment
3534 Elevators & Moving Stairways
3535 Conveyors & Conveying Equipment
3536 Overhead Traveling Cranes, Hoists & Monorail Systems
3537 Industrial Trucks, Tractors, Trailers & Stackers
3541 Machine Tools, Metal Cutting Types
3542 Machine Tools, Metal Forming Types
3543 Industrial Patterns
3544 Special Dies & Tools, Die Sets, Jigs & Fixtures & Industrial Molds
3545 Cutting Tools, Machine Tool Accessories & Machinists' Precision Measuring Devices
3546 Power-Driven Handtools
3547 Rolling Mill Machinery & Equipment
3548 Electric & Gas Welding & Soldering Equipment
3549 Metalworking Machinery, NEC
3552 Textile Machinery
3553 Woodworking Machinery
3554 Paper Industries Machinery
3555 Printing Trades Machinery & Equipment
3556 Food Products Machinery
3559 Special Industry Machinery, NEC
3561 Pumps & Pumping Equipment
3562 Ball & Roller Bearings
3563 Air & Gas Compressors
3564 Industrial & Commercial Fans & Blowers & Air Purification Equipment
3565 Packaging Machinery
3566 Speed Changers, Industrial High-Speed Drives & Gears
3567 Industrial Process Furnaces & Ovens
3568 Mechanical Power Transmission Equipment, NEC
3569 General Industrial Machinery & Equipment, NEC
3571 Electronic Computers
3572 Computer Storage Devices
3575 Computer Terminals
3577 Computer Peripheral Equipment, NEC
3578 Calculating & Accounting Machines, Except Electronic Computers
3579 Office Machines, NEC
3581 Automatic Vending Machines
3582 Commercial Laundry, Drycleaning & Pressing Machines
3585 Air Conditioning & Warm Air Heating Equipment & Commercial & Industrial Refrigeration Equipment
3586 Measuring & Dispensing Pumps
3589 Service Industry Machinery, NEC
3592 Carburetors, Pistons, Piston Rings, & Valves
3593 Fluid Power Cylinders & Actuators
3594 Fluid Power Pumps & Motors
3596 Scales & Balances, Except Laboratory
3599 Industrial & Commercial Machinery & Equipment, NEC

36 Electronic & Other Electrical Equipment & Components Except Computer Equipment

3612 Power, Distribution & Specialty Transformers
3613 Switchgear & Switchboard Apparatus
3621 Motors & Generators
3624 Carbon & Graphite Products
3625 Relays & Industrial Controls
3629 Electrical Industrial Apparatus, NEC
3631 Household Cooking Equipment
3632 Household Refrigerators & Home & Farm Freezers
3633 Household Laundry Equipment
3634 Electric Housewares & Fans
3635 Household Vacuum Cleaners
3639 Household Appliances, NEC
3641 Electric Lamp Bulbs & Tubes
3643 Current-Carrying Wiring Devices
3644 Noncurrent-Carrying Wiring Devices
3645 Residential Electric Lighting Fixtures
3646 Commercial, Industrial & Institutional Electric Lighting Fixtures
3647 Vehicular Lighting Equipment
3648 Lighting Equipment, NEC
3651 Household Audio & Video Equipment
3652 Phonograph Records & Prerecorded Audio Tapes & Disks
3661 Telephone & Telegraph Apparatus
3663 Radio & Television Broadcasting & Communications Equipment
3669 Communications Equipment, NEC
3671 Electron Tubes
3672 Printed Circuit Boards
3674 Semiconductors & Related Devices
3675 Electronic Capacitors
3676 Electronic Resistors
3677 Electronic Coils, Transformers & Other Inductors
3678 Electronic Connectors
3679 Electronic Components, NEC
3691 Storage Batteries
3692 Primary Batteries, Dry & Wet
3694 Electrical Equipment For Internal Combustion Engines
3695 Magnetic & Optical Recording Media
3699 Electrical Machinery, Equipment & Supplies, NEC

37 Transportation Equipment

3711 Motor Vehicles & Passenger Car Bodies
3713 Truck & Bus Bodies
3714 Motor Vehicle Parts & Accessories
3715 Truck Trailers
3716 Motor Homes
3721 Aircraft
3724 Aircraft Engines & Engine Parts
3728 Aircraft Parts & Auxiliary Equipment, NEC
3731 Ship Building & Repairing
3732 Boat Building & Repairing
3743 Railroad Equipment
3751 Motorcycles, Bicycles & Parts
3761 Guided Missiles & Space Vehicles
3764 Guided Missile & Space Vehicle Propulsion Units & Propulsion Unit Parts
3769 Guided Missile & Space Vehicle Parts & Auxiliary Equipment, NEC
3792 Travel Trailers & Campers
3795 Tanks & Tank Components
3799 Transportation Equipment, NEC

38 Measuring, Analyzing & Controlling Instruments; Photographic, Medical & Optical Goods; Watches & Clocks

3812 Search, Detection, Navigation, Guidance, Aeronautical & Nautical Systems & Instruments

NOTE: "NEC" indicates "not elsewhere classified"

Source: Dun's Marketing Services, Inc., Million Dollar Directory 1991, Parsippany, NJ, 1991.

APPENDIX B
TOP 100 DEFENSE CONTRACTORS

Rank	Parent Company	Fiscal 1990 Contract Awards ($000s) Total DOD	Air Force	Army	Navy	R&D	Products	Services	Mkt. Share
1	McDonnell Douglas[1]	$8,923,457	$3,734,271	$1,983,544	$3,139,980	$2,377,435	$6,091,765	$ 454,257	6.7%
2	General Dynamics[2]	6,569,018	3,118,900	1,125,524	2,311,414	904,840	4,867,175	797,003	4.9
3	General Electric[3]	5,823,497	1,964,696	838,431	2,861,003	922,562	4,215,947	684,988	4.3
4	General Motors[4]	4,305,974	1,114,224	1,473,206	1,640,679	373,975	3,255,954	676,045	3.2
5	Martin Marietta[5]	4,246,032	3,113,053	700,798	267,269	2,540,114	1,480,161	225,757	3.2
6	Raytheon[6]	4,166,633	1,276,231	1,101,439	1,778,438	758,614	2,766,147	641,872	3.1
7	Lockheed[7]	3,854,622	1,656,687	439,794	1,738,988	1,416,492	2,101,576	336,554	2.9
8	United Technologies[8]	2,950,932	1,621,273	666,882	655,601	389,018	2,388,922	172,992	2.2
9	Grumman	2,725,294	290,101	110,160	2,255,517	432,042	1,817,936	475,316	2.0
10	Boeing[9]	2,423,547	1,383,354	782,553	248,051	1,004,640	894,071	524,836	1.8
11	Tenneco	2,370,675	0	8,635	2,350,478	22,574	885,750	1,462,351	1.8
12	Westinghouse Electric[10]	2,274,377	955,189	26,221	1,277,342	696,686	1,492,008	85,683	1.7
13	Rockwell International	2,230,389	1,760,854	225,831	233,973	590,437	1,343,995	295,957	1.7
14	Litton Industries	1,562,349	158,320	56,960	1,332,011	287,827	1,120,360	154,162	1.2
15	Unisys	1,457,445	379,517	200,809	844,084	65,758	1,019,969	371,718	1.1
16	GTE	1,304,641	143,223	1,035,595	42,531	118,954	1,008,862	176,825	1.0
17	Textron[11]	1,245,562	161,195	797,216	277,872	164,971	992,526	88,065	0.9
18	IBM	1,235,234	629,488	40,595	523,430	127,045	866,577	241,612	0.9
19	TRW	1,097,223	701,866	287,298	90,892	586,695	259,708	250,820	0.8
20	Gencorp	1,094,966	998,314	92,657	3,995	255,843	158,385	680,738	0.8
21	LTV	1,054,864	18,750	989,800	7,992	212,531	717,468	124,865	0.8
22	ITT[12]	947,110	301,659	262,489	362,129	67,628	613,871	265,611	0.7
23	AT&T	944,756	113,426	66,894	397,647	188,094	252,056	504,606	0.7
24	Foundation Health Corp.	865,272	0	0	0	515,206	0	350,066	0.6
25	Alliant Techsystems[13]	855,841	6,594	586,279	261,275	292,695	537,343	25,803	0.6
26	Ford Motor Co.[14]	799,874	501,431	104,349	155,497	319,036	168,533	312,305	0.6
27	MIT	787,850	764,723	7,015	13,136	783,538	155	4,157	0.6
28	Allied-Signal[15]	783,379	301,812	171,960	275,766	173,413	508,208	101,758	0.6
29	Northrop	748,478	620,651	49,987	76,874	424,574	184,415	139,489	0.6
30	Texas Instruments[16]	745,631	137,569	107,282	488,725	151,371	549,100	45,160	0.6
31	Gibbons, Green & Van Amerongen	737,312	0	0	737,312	0	722,375	14,937	0.5
32	FMC[17]	649 632	-155	428,091	221,412	59,296	554,844	35,492	0.5
33	Teledyne	629,311	259,355	244,789	121,937	201,183	380,811	47,317	0.5
34	Royal Dutch Petroleum	625,205	141	0	0	0	618,018	7,187	0.5
35	Loral[18]	556,846	305,015	90,103	157,341	59,652	450,599	46,595	0.4
36	Honeywell[19]	546,179	217,719	90,017	205,628	111,201	345,802	89,176	0.4
37	Avondale Industries	546,162	0	0	545,775	0	519,441	26,721	0.4
38	Science Applications	503,556	120,769	130,429	168,536	183,528	31,596	288,432	0.4
39	Dyncorp	500,873	178,720	190,725	126,420	7,573	18,610	474,690	0.4
40	Olin	495,557	62,189	406,882	14,954	34,514	292,802	168,241	0.4
41	Hercules	476,047	134,461	290,039	49,481	79,950	174,948	221,149	0.4
42	Exxon	453,084	54	62	485	275	452,090	719	0.3
43	E-Systems	434,446	105,752	186,058	140,779	41,339	72,633	320,474	0.3
44	Penn Central	433,323	61,853	10,609	358,656	16,535	25,696	391,092	0.3
45	Aerospace Corp.	416,217	416,217	0	0	416,217	0	0	0.3
46	Mitre Corp.	412,354	410,791	1,063	0	407,283	0	5,071	0.3
47	Atlantic Richfield	390,312	341	0	-195	592	389,720	0	0.3
48	Johnson Controls	384,041	136,169	231,951	14,501	169,497	2,859	211,685	0.3
49	Computer Sciences[20]	377,650	161,710	47,348	138,225	70,465	72,583	234,602	0.3
50	Johns Hopkins University	374,239	185	1,484	284,032	373,468	0	771	0.3

51	Motorola	357,701	36,889	195,208	112,489	37,717	294,752	25,232	0.3
52	Defense Facilities Admin.[21]	354,752	354,752	0	0	0	0	354,752	0.3
53	Morrison-Knudsen	331,335	0	7,759	308,925	749	265,367	65,219	0.2
54	Coastal Corp.	331,117	1,170	1,058	0	0	327,757	3,360	0.2
55	European Utilities[22]	313,300	0	313,300	0	0	0	313,300	0.2
56	Eaton	304,804	261,897	10,418	14,525	37,308	220,596	46,900	0.2
57	Philips Gloeilampenfabrieken	296,703	103,648	89,460	94,295	61,865	216,803	18,035	0.2
58	Thiokol	290,554	140,884	128,757	20,913	19,584	156,058	114,912	0.2
59	Astronautics Corp. of America	274,721	129,792	46,125	98,259	107,869	142,992	23,860	0.2
60	Canadian Commercial Corp.[23]	259,722	79,574	60,052	72,272	13,038	208,367	38,317	0.2
61	Oshkosh Truck	259,183	39,879	212,500	4,876	31,047	228,136	0	0.2
62	Control Data	243,907	83,939	29,025	128,228	51,609	168,932	23,366	0.2
63	Mobil	237,694	0	0	6,293	0	237,470	224	0.2
64	Chrysler	227,480	151,354	41,362	30,001	23,991	130,506	72,983	0.2
65	CAE Industries	227,359	107,115	32,222	87,984	24,660	174,466	28,233	0.2
66	CSX	225,601	0	0	225,601	0	0	225,601	0.2
67	Kaman	213,623	39,705	65,000	96,292	86,543	79,663	47,417	0.2
68	Peterson Builders	211,643	0	0	211,643	0	211,140	503	0.2
69	Black & Decker[24]	209,721	38,453	33,774	112,813	35,545	2,277	171,899	0.2
70	Forstmann, Little & Co.	199,171	160,859	27,127	5,676	0	36,754	162,417	0.1
71	CRSS[25]	192,302	188,241	2,892	1,169	0	0	192,302	0.1
72	International Marine Carriers	190,924	0	0	190,924	0	0	190,924	0.1
73	Federal Express	190,511	190,511	0	0	0	0	190,511	0.1
74	Chevron	187,751	124	0	0	0	187,614	137	0.1
75	Amoco	186,949	0	0	2,459	2,408	184,541	0	0.1
76	Westmark Systems	185,573	46,812	6,073	132,623	29,776	41,915	113,882	0.1
77	Harris	183,637	93,345	47,274	38,799	28,239	105,023	50,375	0.1
78	Harsco[26]	179,382	3,675	168,206	2,029	71,315	107,394	673	0.1
79	Bollinger	166,791	0	0	166,791	0	166,791	0	0.1
80	SNECMA[27]	159,291	159,291	0	0	0	159,291	0	0.1
81	Rolls Royce.	157,831	4,394	249	153,188	249	149,307	8,275	0.1
82	Plessey Co.	155,943	132,869	17,069	5,870	117,112	34,954	3,877	0.1
83	Logicon	152,688	50,987	35,419	37,399	69,747	10,844	72,097	0.1
84	Varian Associates	151,562	14,729	60,542	59,300	5,106	125,841	20,615	0.1
85	World Airways	144,891	144,891	0	0	0	0	144,891	0.1
86	Day & Zimmermann	141,703	0	116,044	25,659	323	7,153	134,227	0.1
87	MIP Instandsetzungsbetric	138,857	0	138,857	0	0	0	138,857	0.1
88	Digital Equipment Corp.	135,905	61,904	10,113	53,309	5,596	96,034	34,275	0.1
89	Hewlett-Packard	131,939	54,835	16,877	55,129	1,739	124,990	5,210	0.1
90	Brand Name Contractor[28]	129,322	0	129,322	0	0	129,322	0	0.1
91	Eastman Kodak Co.	125,588	9,631	88,647	21,280	5,295	29,309	90,984	0.1
92	Amerada Hess	124,708	0	0	0	0	124,582	126	0.1
93	Esco Electronics[29]	124,171	37,801	53,526	32,699	14,072	109,991	108	0.1
94	Nichols Research	124,046	10,446	69,893	4,934	115,076	2,525	6,445	0.1
95	United Industrial	123,784	39,413	14,925	69,440	18,793	51,323	53,668	0.1
96	Goodyear Tire & Rubber	120,387	34,202	84,268	1,669	0	120,234	153	0.1
97	Enserch	117,341	3,424	106,727	2,054	5,060	0	112,281	0.1
98	Contel	117,268	52,188	7,292	30,750	19,452	32,904	64,912	0.1
99	Duchossois Industries	112,206	0	101,925	10,098	15,315	38,668	58,223	0.1
100	Norfolk Shipbuilding Dry Dock	111,266	0	0	111,266	0	0	111,266	0.1

Source: Government Executive (August 1991)

VITA

Richard B. Collins, II was born June 28, 1956 to Richard and Anita Collins in San Rafael, California. He received a B.A. in Economics from Wake Forest University in 1978.

For the last eleven 11 years, he has worked in industry and government as a weapon system cost analyst. Mr. Collins is currently employed by the Naval Center for Cost Analysis (NCA), a field agency of the Comptroller of the Navy which performs Navy weapon system cost estimation, Navy contract performance measurement and Navy contractor financial analysis. He is responsible for developing cost estimating methodology and cost estimates for ships and ship systems (e.g., sonar, radar, guns, etc.).

Prior to joining NCA in 1989, Mr. Collins was employed by Science Applications International Corporation (SAIC). As a member of the Economic Analysis Division, he specialized in the development of cost databases and cost estimating methodology for electronics, missiles, torpedoes and aircraft. This work was performed for a variety of DOD and industry clients.

Richard B. Collins II