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Forecasting Bankruptcy Within Department of Defense Suppliers Using Linear Discriminant Analysis

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Abstract: Annually, purchasing divisions within the Department of Defense (DoD) analyze their needs and decide whether to renew existing contracts or sign new contracts with government suppliers. Supplier financial stability is a concern when assessing such contracts for selection. This paper presents an accurate bankruptcy risk assessment model that examines financial stability. Though several bankruptcy models exist in literature, a standard model is not accepted across the DoD. In this work, we build two new samples of DoD bankrupt and nonbankrupt firms consisting of respective financial and accounting variables drawn from 10-K statements. We then train, validate, and test a novel linear discriminant model using a subset of such variables. We evaluate the new model's accuracy alongside popular bankruptcy models in literature for comparison. When using the DoD samples, this new model outperforms the models from literature and shows promise to make a significant impact on the DoD procurement process.

Keywords: Bankruptcy, Financial Distress, Prediction, Department of Defense, Multilinear Discriminant Analysis

1. Background & Literature Review

Financial risk is a critical component of supply chain risk. A company that is unable to fulfill its contractual obligations due to insolvency or bankruptcy can compromise an entire downstream supply chain. Identifying, assessing, and mitigating supply chain risk is especially important within the U.S. Department of Defense (DoD). Furthermore, the underlying commercial industrial base forms the foundation of national security. The nature of military operations requires timely and precise production and delivery of equipment, parts, weapons, and ammunition throughout the supply chain. Ernst and Young identified supply chain issues as posing the 2nd greatest risk to aerospace and defense companies (Maiti 2017). In addition, they note that the changing economic environment and reductions in defense budgets may adversely affect the financial health of suppliers (Maiti 2017). The 2021 Global Aerospace and Defense Industry Outlook projects potential for some defense suppliers to face cost increases and schedule delays because of the COVID-19 pandemic (Coykendall et al 2020). Additionally, the report notes that under the new Biden administration, defense budgets for fiscal year 2022 and beyond could fall as funds are shifted toward social and domestic programs (Coykendall et al 2020). These events, combined with uncertainty in the domestic and international political landscape, could hurt DoD suppliers' bottom line. Providing a reliable and efficient method of assessing the financial stability of a DoD supplier is critical to maintaining military readiness. This study builds a predictive classification model which predicts bankruptcy and provides an early supplier financial distress warning to U.S. government purchasers.

Currently, before vendors are selected to take on a government contract, they must pass a series of evaluations that examine their operations and reliability (Moses & Liao, 1986). The U.S. government uses performance-based contracting (PBC), which ties payment to performance rather than input, activities, and tasks (Kim et al., 2007)—allowing the DoD to mitigate risk and place it on contractors to develop and deliver weapon systems. Using PBC, the risk moves away from the customer and to the contractor (Kleemann & Essig, 2013). The conditions that follow for contract termination rely on either the failure of that contractor to meet its obligations or the rise of a more promising prospect.

Beginning in the 1990s, some government organizations went beyond PBC and employed empirical models to evaluate the financial health of government contractors. For instance, the Defense Contract Audit Agency used Altman's five variable model (1968) to assess the financial health of defense corporations. The Department of the Navy used Dagel and Pepper's model (1990) to evaluate those firms contracting with their branch of service (Bowlin 1995). Similarly, guidance published by the Defense Contract Management Command recommended using Altman's (1968) model and ratio analysis (Candreva 1996). Liao and Moses (1987) and Godfrey (1990) also used a sample of defense contractors to successfully build their classification models. Each of these models can be characterized by various attributes such as training sample size & composition, type & number of independent variables, modeling technique, length of period between prediction & bankruptcy, and validation method. In this study, we pull various features from these models and incorporate them into constructing a novel model utilizing factors that appear consistently throughout the literature and lead to an increase in model accuracy.

Most models found in the literature assessed financial stability from 1 to 5 years before bankruptcy. A model that can predict bankruptcy up to 5 years before the event is useful for obvious reasons. However, the literature shows that attempts to predict bankruptcy more than two years prior are unsuccessful. Of the models that used data for multiple years prior to failure, the accuracy declines significantly as the prediction time horizon increases. Altman's (1968) model was 95% accurate in predicting failure one year before bankruptcy, 72% accurate two years prior, and only 36% correct five years prior. Other notable studies, such as Dagel & Pepper (1990) and Liao & Moses (1987), opted for predicting failure one year prior. Our analysis follows suit and creates a forecast based on data collected for one year prior to bankruptcy.

When training a model, the type of companies comprising the sample and the sample's size greatly impact model accuracy and usability. Larger samples are beneficial as they more closely approximate the population. Additionally, the data comprising the sample should be as reflective of the underlying population as possible. In choosing their data sample, Dagel and Pepper (1990) found that it was impossible to create a sufficient sample of bankrupt DoD firms as so few had filed for bankruptcy at the time (Collins 1991). To reach a sufficient sample size, Dagel and Pepper (1990) included other manufacturing firms that were comparable in nature to defense contractors (Collins 199). Model accuracy can fall significantly when tested on a sample different from its initial training and validation sets. However, when Bowlin (1995) tested Dagel and Pepper's model on a sample comprised of companies from the same industry as its training set, he found that the model was only 68% accurate at predicting bankruptcy using a newer sample of aerospace and defense firms. More concerningly, with a separate sample, Godfrey (1990) determined the model accurately predicted bankruptcy just 44% of the time. For her own model, Godfrey (1990) was only able to obtain financial information from five of a proposed set of 150 bankrupt defense contractors. To solve the issue, Godfrey (1990) included bankrupt companies likely to do business with the government in her sample.

Beyond the DoD, more recent studies have shown that Machine learning techniques to predict bankruptcy can be more successful than traditional models such as linear regression, and logit models used in the models discussed above. (du Jardin 2016, Wang et al. 2014). However, machine learning methods are not without fault and there is still debate to whether a truly superior type of model exists (Barboza et al., 2017). To our knowledge the DoD has not implemented any bankruptcy models rooted in machine learning techniques.

Overall, the literature shows that previous models are no longer sufficient at predicting bankruptcy for current DoD vendors. It is not known if the models can accurately assess the financial health of firms today as the time period of the observations along with the introduction of new financial situations significantly impacts a model's predictive power (Grice and Dugan, 2001). For assessing firm bankruptcy in the present period, Bellovary suggests analysis and refinement of existing models using contemporary data (2007). We answer this call for new model development and Grice's call to assess historical models. Prior to developing a new model, this study evaluated the accuracy of previous bankruptcy classification models found in the literature with new samples comprised of recent DoD contractor data. This same data was used to train, validate, and test the new model allowing for a comparison of performance and effectiveness against the older models. A lack of sufficient data concerning bankrupt defense contractors led to previous models being trained with non-defense data, impacting their reliability in practice. Given the growth in the availability and accessibility of defense bankruptcy data over the past several decades, this study includes data solely from defense contractors in the samples used to evaluate previous models in the literature and to construct and test a new model.

2. Collection of Data

To create a new financial distress model, our team developed data samples from bankrupt and nonbankrupt companies contracted with the DoD. We utilized public sources to collect data and constructed a list of DoD contracting companies that have declared bankruptcy since 2007. We then matched each bankrupt company to a company contracting with the DoD of similar size and revenue which has never declared bankruptcy. To match companies, a factor of ten is used when comparing revenues. For example, a bankrupt firm with a revenue of one million was matched with a nonbankrupt firm with revenue from \$100,000 to \$10,000,000. While this seems like a large range, note that most of our matched pairs were separated by less than a factor of two. According to Theiler (2013), classification problems with a matched-pair structure in the training data have significantly better classification accuracy. We examined a myriad of historical forecasting models used to predict bankruptcy and consolidated the financial variables and ratios used and included these factors in our sample for each bankrupt and nonbankrupt company. We sourced our data from S&P Global CapitalIQ, a platform that provides financial and market information for public corporations. Our matched pair sample, Sample 1, was used to train and validate the model. Later, a secondary sample of DoD data containing bankrupt and nonbankrupt companies, Sample 2, was used to test the model. This second sample was not matched in revenue, personnel, or industry.

3. Approach and Methodology

The most successful bankruptcy models are distinct types: one a logit model, one a machine learning model and the other being a linear classification model (Ohlson 1980, Barboza 2017, Altman 1968). Since all three types of models proved successful historically, we developed our own separate logistic regression, machine learning and linear classification models to determine which produced the most accurate forecasting with contemporary DoD supplier data. After several iterations of testing the data on new models, we determined the best forecasting model to be a linear classification model using linear discriminant analysis, which frequently appeared in literature as a viable method for developing bankruptcy prediction algorithms (Altman 1968, Dagel and Pepper 1990, Moses and Liao 1987). Linear discriminate analysis uses a linear equation to compute the dependent variable which is then compared to a specific threshold value to classify the observation into groups. Discriminant analysis is a statistical technique that computes the optimal combination of independent variables and their coefficients such that the ratio of the mean sum of squares between groups to the mean sum of squares within groups is maximized (Collins 1991). For this model, the independent variables consisted of publicly available financial and accounting data. The classification categories were bankrupt or nonbankrupt. In training the model, the set of possible financial variables and ratios to be included consisted of 33 that previously appeared in the literature. However, financial ratios are often highly correlated, impacting model performance (Candreva 1996). Before model training, we also assessed variable collinearity using a correlation matrix (Friendly and Kwan 2009). If the mean absolute correlation between two variables was more significant than 0.75, it was removed as a candidate factor. The model was trained and validated on a matched sample of 27 bankrupt and 27 nonbankrupt companies (Sample 1). To train and test the model, we employed five-fold cross validation which evaluated the model accuracy across five subsets of the data as this is an effective technique to prevent overfitting (Frydman, Altman, Kao 1985). In training the model, we assessed variable importance using the absolute value of the t-statistic for each model parameter (Kuhn 2021). If a variable's importance was significantly low, we removed it as a potential factor and re-trained the model. After accounting for multicollinearity and variable significance, the model (1) discriminant function takes the form:

$$Y = 2.919078E^{-12}X_1 + 1.172303E^{-9}X_2 - 6.374902E^{-2}X_3 - 2.204218E^{-1}X_4 \tag{1}$$

X_1 = Current Assets
X_2 = Net Income
X_3 = Total Liabilities / Total Assets
X_4 = Current Liabilities / Current Assets
Y = Classification Score

The average accuracy across the five validation folds was 90.5%. Satisfied with these results, we then tested the model against a different sample comprised of 37 bankrupt and nonbankrupt DoD suppliers (Sample 2). The new model accuracy rate for Sample 2 was 94.44%. Notably, the model predicted just one false negative. Thus, the Type II error rate was 6.7%. A false negative in this context means a potentially distressed supplier is falsely classified as financially healthy. In this study, failure to correctly classify a financially distressed company as bankrupt can cause significant harm through supply chain disruption and excess costs. Therefore, a model that has minimal Type II error is most effective.

4. Results and Analysis

We tested the samples on existing models found in the literature for comparison once we gathered and formatted the data. Each of the models from Dagel & Pepper (1990), Liao & Moses (1986), Godfrey (1991), Ohlson (1980), and Altman (1968) are either linear classification or logit models. We tested the models using both Sample 1 and Sample 2, then calculated an accuracy score for both. Testing the sample sets on the historical models proved that these models are insufficient in predicting bankruptcy today. Overall, the existing models predict bankruptcy with lower accuracy than previously reported in

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their papers. Table 1 shows the prediction accuracies of each historical model compared to the prediction accuracy of our model. The existing models predict bankruptcy at lower accuracy levels than previously reported, likely due to the fact Samples 1 & 2 include contractors across multiple industries and time periods. The previous models were developed to fit a particular time period or industry, causing limited prediction ability. Authors in literature have called for new models that are insensitive to time (Bellovary 2007). The new model we developed fills this gap in the literature. Government contracting agencies, such as the U.S. Combat Capabilities Development Command's (DEVCOM) Aviation and Missile Center (AvMC), expect a prediction model to forecast bankruptcy at a rate higher than 80% indicating a need for our model in practice.

Table 1. Accuracy of Previous Bankruptcy Forecasting Models and Our New Model

Accuracy of Models	**Dagel & Pepper**	**Liao & Moses**	**Godfrey**	**Ohlson**	**Altman**	**Our Model**
Matched Sample	56%	70%	57%	80%	74%	91%*
Non-Matched Sample	57%	74%	55%	80%	86%	94%
Average Accuracy	56.5%	72%	56%	80%	80%	92%

**Our prediction of the matched sample consisted of the average accuracy across the five folds used in cross validation*

The Ohlson (1980) and Altman (1968) models consistently performed well across both datasets based on the results of our testing. However, there is still room for improvement. This aligns with the literature, as these two models have been successfully applied outside their original application sample. These models shared many of the same variables, as seen in Table 2 which shows the variables that each historical model utilizes to predict bankruptcy alongside the variables chosen for our new model.

Table 2. Variables Included in Each Bankruptcy Forecasting Model

Model Variables	**Dagel & Pepper**	**Liao & Moses**	**Godfrey**	**Ohlson**	**Altman**	**Our Model**
Total Debt	✓					
Total Assets	✓	✓	✓	✓	✓	✓
Current Assets	✓			✓		✓
Quick Assets	✓					
Total Liabilities		✓		✓	✓	✓
Current Liabilities	✓			✓		✓
Working Capital	✓	✓		✓	✓	
Retained Earnings		✓			✓	
Cash Flow	✓			✓		
Total Revenue	✓	✓			✓	
Net Income				✓		✓
YEAR PRIOR Net Income				✓		
Earnings Before Interest & Taxes		✓			✓	
Market Value of Equity		✓			✓	
GNP Price Index				✓		
Cash			✓			

The model we developed is a linear classification model that uses linear discriminant analysis. Our model produced over 90% average accuracy on five different subsets of Sample 1 through five-fold cross validation. In Sample 2, the model was 94% accurate in predicting bankruptcy. The new model outperformed all previous models across both samples. This is not unexpected as our model includes some of the same variables as the successful Ohlson (1980) and Altman (1968) models. Table 3 shows which models utilized accounting variables and which models utilized market variables. Our model purposely does not use market variables because many companies contracted with the DoD are private. Therefore, our model is still able to predict bankruptcy of private companies since no market data is needed. While our study does not include private firms in the samples, we wanted to keep the option open for future research. Furthermore, we trained our model with a diverse dataset spanning multiple decades and industries, indicating that our model is not as sensitive to time as previous models. While all firms used to train the dataset contracted with the DoD, they came from a variety of sectors such as aerospace, energy, software, construction, and manufacturing. The training set included data from different economic environments, such as before, during, and after, periods of downturn, namely as the 2008 financial crisis and COVID-19 pandemic. It represents a key development in the analysis of defense suppliers as the model should continue to be an accurate forecasting tool across fluctuating economic conditions.

Table 3. Basic Attributes of Each Bankruptcy Forecasting Model

Model Attributes	Dagel & Pepper	Liao & Moses	Godfrey	Ohlson	Altman	Our Model
Linear Classification	✓	✓	✓		✓	✓
Logit Model				✓		
Accounting Variables	✓	✓	✓	✓	✓	✓
Market Variables		✓		✓	✓	

An example of where the model could have prevented a critical supply chain issue, is the bankruptcy of NorthStar Aerospace, a U.S. Army supplier (DEVCOM 2021). AvMC was responsible for overseeing the successful fulfilment of its obligations. Additional customers of NorthStar include other suppliers with DoD contracts such as Sikorsky Aircraft. Additionally, Boeing, another major DoD supplier, was the company's largest unsecured creditor. NorthStar's main obligation was to provide the Army with gears for Blackhawk helicopters. In 2012, the company filed for Chapter 11 bankruptcy halting operations and leading to significant aviation supply chain disruptions for the Army. Not only was NorthStar unable to fulfill its contracts to the government, but its financial failure also created risk for other firms in the defense aviation supply chain. AvMC was not properly equipped with the tools or resources to anticipate this bankruptcy and take preemptive action. Given its financial condition, our model would have successfully predicted that NorthStar was going to file bankruptcy one year prior to doing so, allowing AvMC time to implement proactive risk mitigation measures.

5. Conclusions and Future Research

This model is an effective tool which can augment existing methods for assessing contractors' fulfillment ability across the federal government. Since this model was developed and tested on defense contractor data not exclusive to the aerospace industry, its use can be extended to other agencies and organizations across the DoD. The model proves, through validation and testing, to provide an accurate indicator that a supplier is at risk of going under within the next year. Its effectiveness largely lies in its simplicity and ease of use. To assess bankruptcy risk, analysts only need to pull five items from a company's financial statements and input them into a spreadsheet. Absent any market variables, the model can be used for both private and public corporations. Using a simple function to compute the classification score allows agencies to quickly obtain a bankruptcy prediction. Managers can then conduct additional analysis and investigation in accordance with their organization's policy to determine if action should be taken.

Further testing of our model would provide more comprehensive results on its effectiveness. For our project, we focused on testing the model with Department of Defense data. To ensure the model holds up across multiple industries, further testing with non-DOD data is required. Future research should focus on using datasets comprised of both public and private companies not contracted with the DOD to assess our model on a larger scale. Validating our model with non-DOD companies will ensure that its prediction capability is applicable to anyone seeking to forecast bankruptcy.

No prediction model can ever be perfect. Although our model is highly accurate and effective at predicting financial bankruptcy, supply chain disruption risk is not solely based on financial status. A multitude of factors contribute to the risk associated with supply chain disruption, such as natural disasters, and labor disputes. Further research that encompasses additional risk factors, and includes bankruptcy risk, must be completed to build a holistic, more accurate assessment of risk. Our bankruptcy model could serve as a key puzzle piece in the development of a supplier risk framework that spans several risk categories.

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6. References

Altman, E. I., Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, Vol. XXIII, No. 4, Sept. 1968, pp. 589-609.

Barboza, F., Kimura, H., Altman, E. (2017). Machine learning models and bankruptcy prediction. *Expert Systems with Applications*, 83, 405–417. https://doi.org/10.1016/j.eswa.2017.04.006

Bellovary, J.L., Giacomino, D.E. & Akers, M.D. (2007) A Review of Bankruptcy Prediction Studies: 1930 to Present. *Journal of Financial Education,* Vl. 33, pp. 1-42.

Bowlin, W. F. (1995). An Empirical Comparison of Models for Identifying Fiscal Stress in the Defense Industry. *The Journal of Cost Analysis, 12*(1), 105-129. doi:10.1080/08823871.1995.10462294.

Candreva, P. J. (1996). The Use of Financial Scoring Models for the Prediction of Business Failure: Implications for Department of Defense Financial Analysis. *(Master's thesis).* Naval Postgraduate School.

CapitalIQ. *S&P Global Market Intelligence*. https://www.capitaliq.com/.

Collins, R. B. (1991). Evaluation of a Financial Distress Model for Department of Defense Hardware Contractors (Unpublished master's thesis). Virginia Polytechnic Institute and State University.

Coykendall, J., Condro, M., Faver, A., & Shepley, S. (2020). *2021 Aerospace and Defense Industry Outlook* (Rep.). New York, NY: Deloitte.

Dagel, H. W., & Pepper, R. M. (1990). A Financial Distress Model for DoD Hardware Contractors. *Journal of Parametrics, 10*(1), 5-40. doi:10.1080/10157891.1990.10462471.

DEVCOM (2021). Discussions with U.S. Army Combat Capabilities Command Leaders. *Huntsville, AL*. November 2021.

du Jardin, P. (2016). A two-stage classification technique for bankruptcy prediction*. European Journal of Operational Research*, 254(1), 236–252. https://doi.org/10.1016/j.ejor.2016.03.008

Friendly, M., & Kwan, E. (2009). Where's Waldo? Visualizing Collinearity Diagnostics. *The American Statistician*, *63*(1), 56–65. http://www.jstor.org/stable/27644096.

Frydman, H., Altman, E., & Kao, D. (1985). Introducing recursive partitioning for financial classification: The case of financial distress. *The Journal of Finance*, 40(1), 269–291. https://doi.org/10.1111/j.1540-6261.1985.tb04949.x

Godfrey, I. C. (1990). Predicting bankruptcy in the Air Force. *(Master's thesis).* Air Force Institute of Technology.

Grice, J. S. & Dugan, M. T. (2001). The Limitations of Bankruptcy Prediction Models: Some Cautions for the Researcher. *Review of Quantitative Finance and Accounting*. 17, 2; ABI/INFORM Collection pg. 151

Kim, S.-H., Cohen, M. A., & Netessine, S. (2007). Performance Contracting in After-Sales Service Supply Chains. *Management Science*, 53(12), 1843–1858. https://doi.org/10.1287/mnsc.1070.0741

Kleemann, F. C., & Essig, M. (2013). A providers' perspective on supplier relationships in performance-based contracting. *Journal of Purchasing and Supply Management*, 19(3), 185–198. https://doi.org/10.1016/j.pursup.2013.03.001

Kuhn, Max. (2021). caret: Classification and Regression Training. *R package version 6.0-90*. https://CRAN.R-project.org/package=caret

Maiti, S. (2017). Top 10 Risks in Aerospace and Defense (A&D) (Rep.). New York, NY: Ernst and Young.

Moses, D., & Liao, S. (1986). On Developing Models for Failure Prediction. *Journal of Commercial Bank Lending, 69*, 27-38.

Ohlson, J.A. (1980) Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 18, 109-131. http://dx.doi.org/10.2307/2490395.

Theiler, J. (2013). Matched-pair machine learning. *Technometrics*, 55(4), 536–547. https://doi.org/10.1080/00401706.2013.838191

Wang, G., Ma, J., & Yang, S. (2014). An improved boosting based on feature selection for corporate bankruptcy prediction. *Expert Systems with Applications*, 41(5), 2353–2361. https://doi.org/10.1016/j.eswa.2013.09.033