The Effects of Client Size and Stress Criteria on Bankruptcy Prediction Models: An Empirical Analysis

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ABSTRACT: This study analyzes the effects of stress level and client size on the power of bankruptcy prediction models. First, four different stress criteria are tested regarding their effectiveness in increasing bankruptcy prediction models’ power. These four criteria are: 1. Auditor View Criterion, 2. Altman Z-score Criterion, 3. Zmijewski Probability Criterion, 4. Stock Return Criterion. I find that Criteria 3 and 4 significantly outperform the other two criteria. The model’s performance is even better when I create a new stress criterion by combining Criteria 3 and 4. Secondly, I find that the traditional wisdom that larger firms are generally less likely to go bankrupt does not hold for stressed firms. This study documents a positive relationship between firm size and the probability of bankruptcy for stressed firms, and provides relevant explanations. Third, I hypothesize and find that firm size has a significant impact upon the relationship between the probability of bankruptcy and other bankruptcy predictors. The interaction terms between firm size and other predictors add significant incremental explanatory power to bankruptcy prediction models.

Key Words: Bankruptcy Prediction; Stress; Firm Size
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1. Introduction

SAS 59 (AU341) requires the auditor to evaluate whether there is a substantial doubt about a client’s ability to continue as a going concern for at least one year beyond the balance sheet date. An inaccurate judgment on a client’s financial viability causes serious consequences. The issuance of a going concern opinion to a subsequently surviving client can lead to losing the client; while the failure to issue a going concern opinion to a subsequently bankrupt firm can cause huge litigation costs and reputation damages for auditors (Palmrose 1987). In today’s dynamic economic environment, the number and the magnitude of bankruptcy filings are increasing significantly. Even though auditors possess expertise in making the going-concern judgment, and have good knowledge of firms’ situations, they often fail to give going concern opinions prior to clients’ bankruptcies. Due to the importance and difficulty in evaluating clients’ financial viability, bankruptcy prediction models have become important decision aids for auditors. These models are also useful for other stakeholders of organizations including managers, shareholders, debt-holders and potential investors, as well as academic researchers.

This study empirically tests the effects of client stress level and client size on the performance of bankruptcy prediction models. First, research has shown that the partitioning of a sample into stressed and nonstressed groups improves the models’ prediction accuracy. One major advantage of the partitioning is to “enhance statistical estimation of the model by increasing the within-group sample homogeneity and, consequently, the explanation power.”

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1 In 54 percent of the 673 largest bankruptcies of public companies since 1996, auditors provided no cautions in annual financial statements in the months before the bankruptcy filing, according to Bloomberg. (See http://www.cfo.com/article/1,5309,7123,00.html)
(Hopwood et al. 1994, pp 412) However, researchers have employed various criteria to measure stress. Do these criteria differ in increasing the homogeneity within groups and therefore enhancing models’ prediction power? This study empirically tests this question. Stress Criteria examined include the Auditor View Criterion (Mutchler 1984, 1985; Hopwood et al. 1994; Fleak and Wilson 1994; Foster et al. 1998), two Prediction Model Criterion (Altman Z-score Criterion, Altman 1968; Zmijewski Probability Criterion, Zmijewski 1984, Carcello and Neal 2000), and the Stock Return Criterion (Clark & Ofek 1994).

Second, traditional wisdom and some prior research (See, e.g., Ohlson 1980) suggest larger firms are less likely to go bankrupt. This study proposes that the relation between size and bankruptcy varies along with firms’ stress level. Large firms are usually well developed and operated and relatively stable. Therefore, they do not get into trouble as easily as those small ones. Once they do, it can signal a more serious situation. It also is harder for large firms to recover from stress because more resources are needed. I expect that for firms that are in stress, larger ones are more likely to go bankrupt. Third, firm size (proxy as logarithm of total assets, logarithm of sales, etc.) has been used as an important individual predictor of bankruptcy in prior research (See, e.g., Ohlson 1980). Since firms with different sizes may require different conditions (e.g., leverage level, liquidity level, earning level) for survival, I expect firm size impacts the relation between bankruptcy and other firm characteristics. Whether and to what degree such an impact exists has not been explored by prior studies. In this study I empirically test whether prediction models’ power will be enhanced by incorporating the impact of size upon the relation between bankruptcy and other firm characteristics.
The remainder of this paper is organized as follows. Section 2 provides a literature review. In section 3, I discuss research questions and specify hypotheses. In section 4 I describe the data sample and describe model variables and the research conduction process. In section 5 I present results, while section 6 concludes the paper.

2. Prior Literature

The literature on bankruptcy prediction is extensive. Formal quantitative studies aimed at predicting company bankruptcy have been conducted since the 1930s. A study by Winakor and Smith (1935), and several later ones, concluded that failing firms exhibit significantly different financial ratio measurements than non-failed firms. Later, univariate analysis that used financial indexes based on accounting data was imported into bankruptcy prediction research. Beaver (1966) compared patterns of 29 ratios in the five years preceding bankruptcy, for a sample of failed firms, with a control group of firms that did not fail. “Cash flow/Total Liabilities” proved to be the best predictor overall.

During the late 1960s and throughout the 1970s, multiple discriminant analysis (MDA), a multivariate statistical technique, was used to develop bankruptcy prediction models. One of the best-known MDA bankruptcy prediction models is Altman’s Z-score (Altman 1968). Altman developed his Z-score model by using manufacturing firms that filed a bankruptcy petition under Chapter X of the national bankruptcy act from 1946 to 1965.2 Explanatory variables used in Altman’s model include Net Working Capital/Total Assets, Earnings Before Interest and Taxes/Total Assets, Retained Earnings/Total Assets, Market Value of Equity/Book Value of

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2 Before Chapter 11 of the Bankruptcy Reform Act of 1978 existed, there were three chapters of bankruptcy: Chapters X, XI and XII, for company bankruptcies that involved reorganization. Chapter X involved reorganization for big companies that had public debt or equity, Chapter XI was for readjustment of debts of smaller, non-publicly held companies, and Chapter XII was for companies with extensive holdings of real estate property.
Total Liabilities and Sales/Total Assets. Altman found that all firms with Z-scores greater than 2.99 clearly fell into the non-bankrupt group, while all firms with Z-scores less than 1.81 went bankrupt within the following year. Firms with Z-scores between 1.81 and 2.99 fell into a ‘gray area’ where misclassifications often arise. He found that a cutoff of Z-score equal to 2.675 minimized the total of type I and type II errors.

ZETA (Altman et al. 1977) is another well-known bankruptcy prediction model developed with MDA. ZETA was developed based on a sample of 53 bankrupt firms, of which 29 were manufacturers and 24 were retailers, using data from 1962 to 1975. It is a seven-variable model, including Earnings before Interest and Taxes/Total Assets, Stability of Earnings, Earnings before Interest and Taxes/Total Interest Payments, Retained Earnings/Total Assets, Current Ratio and Common Equity/Total Capital.

Beginning in the 1980s more complex estimation methods such as Logit and Probit were used to determine the likelihood of company bankruptcy. Ohlson (1980) used a logit model to examine the probability of bankruptcy. His sample included 105 bankruptcies and 2058 non-bankruptcies. He found that using a probability cutoff of 3.8 percent for classifying firms as bankrupt minimized type I and type II errors. At this probability cutoff point, the model correctly classified 87.6 percent of his bankrupt firm sample and 82.6 percent of the non-bankrupt firms. In his study, Ohlson found that firm size has a negative relation with the probability of bankruptcy. Begley et al. (1996) applied Altman’s MDA model (1968) and Ohlson’s logit model (1980) to predict bankruptcy for a holdout sample of 65 bankrupt and 1,300 non-bankrupt firms in the 1980s. They found substantially higher type I and type II error rates than those in the original studies. They re-estimated the coefficients for each model using data for a portion of
their 1980s sample. They found no performance improvement for the re-estimated Ohlson Model and marginal performance improvement for the re-estimated Altman model.

Shumway (2001) employed a discrete hazard model. His model used multiple years of data for each sample firm, and treated each firm as a single observation. The study employed all available firms in a broad range of industries, resulting in a sample of 300 bankrupt firms for the period of 1962-1992. The study found that a hazard model out-performed MDA and logit models, and that a combination of market-based and accounting-based independent variables out-performed models that were only accounting-based.

The studies reviewed above focused on the discrimination between bankrupt firms and randomly selected non-bankrupt (including both stressed and nonstressed) firms. Recently, researchers (Wood and Piesse 1987, Hopwood et al. 1994) have suggested stratifying samples based upon client stress levels. For instance, Wood and Piesse (1987) argued that a bankruptcy prediction model developed from a sample of only stressed firms is valuable because it can discriminate between ‘at risk’ firms that survive and ‘at risk’ firms that fail. Hopwood et al. (1994) suggested that the partitioned samples based upon stress levels provided a better framework to study the auditor going concern decision. They hypothesized and found that the partitioning of a sample into stressed and non-stressed groups could increase the sample homogeneity and therefore improved the models’ prediction accuracy. The stress criterion used in their study was the Auditor View Criterion. Specifically, Hopwood et al. (1994) used seven bankruptcy predictors and a stress dummy variable (1 if stressed; 0 otherwise) to form a so-called “restricted model”. Then they formed an “unrestricted model” by adding to the “restricted model” the interactions between the stress dummy variable and seven bankruptcy predictors. These interaction terms were found to have a significant incremental explanatory power above
the “restricted model”. They also found that when applying to the holdout stressed sample, the “unrestricted models” have a significantly lower estimated misclassification cost than the “restricted model”. The suggestion of partitioning study samples based upon clients’ stress level has been followed by later research that study auditor going concern opinions (e.g., Fleak and Wilson 1994; Foster et al. 1998; Carcello and Neal 2000) and bankruptcy prediction models (e.g., Gilbert et al. 1990). Next, I turn now to a discussion of the research issues addressed by the current study.

3. Research Hypotheses

Research has shown that the partitioning of a sample into stressed and nonstressed groups improves the power of bankruptcy prediction models. One major advantage of the partitioning is that “to the extent that the economic circumstances of the stressed and nonstressed groups do differ, it should enhance statistical estimation of the model by increasing the within-group sample homogeneity and, consequently, the explanation power” (Hopwood et al. 1994, pp 412).

Various criteria exist to measure stress. Which existing criterion is better in increasing the homogeneity within groups and therefore enhancing the prediction power is unknown. This study empirically tests this question. The following criteria for stress are identified through literature review and are tested in this study. Stress Criterion 1: The Auditor View. According to this criterion, a company is classified in the stressed category if it exhibits at least one of the following financial distress signals: negative working capital, a loss from operations, a retained earnings deficit, a bottom line loss. I call this stress criterion the Auditor View criterion because it originates from an interview & questionnaire process conducted by Mutchler (1984), using sixteen partners, two from each of the Big Eight accounting firms. This criterion is most widely used in bankruptcy prediction and auditor going concern studies (See, e.g., Mutchler 1984, 1985;
Hopwood et al. 1994; Fleak and Wilson 1994; Foster et al. 1998). Criterion 2: The Altman Z-score. Altman (1968) finds that firms with Z-scores exceeding 3.0 clearly fall into the nonbankruptcy group, while firms with Z-score smaller than 3.0 belong to either the bankruptcy group (those with Z-score < 1.88) or the “gray area” (those with 1.88 < Z-score < 3). Therefore, criterion 2 states that firms with Altman Z-score (1968) smaller than 3 are considered as stressed. Criterion 3: The Zmijewski Probability. Based upon this criterion, a company is considered as stressed if it has a probability of bankruptcy, calculated from Zmijewski’s (1984) model, larger than 28 percent. To analyze the relation between audit committee composition and auditor going concern opinions, Carcello and Neal (2000) use this criterion to select their stressed sample. Both criteria 2 and 3 are based upon prior bankruptcy prediction models derived from firms’ financial information. Criterion 4: Stock Return. This criterion says that a company is categorized as stressed if its market-adjusted return is –15 percent or less in the year prior to the event. To analyze the role of mergers in restructuring distressed firms, Clark & Ofek (1994) use this criterion as an initial screening procedure to identify a potential sample of stressed firms. Unlike the first three criteria, Criterion 4 is based upon stock information instead of financial information. Since no theory or empirical evidence currently exists to favor one criterion over the others, I form the first hypothesis in a null form as follows:

**HYPOTHESIS 1.** *Four proposed stress criteria do not differ in improving the power of bankruptcy prediction models.*

Since larger firms tend to be more diversified and more likely to obtain loans, they are less prone to bankruptcy. The negative relation between firm size and the likelihood of bankruptcy has been confirmed by several prior studies (See, e.g. Ohlson 1980; Begley et al. 1996). However, I expect this negative relation between firm size and the likelihood of
bankruptcy does not hold for a sample of stressed firms. Although larger firms are less likely to fail in general, once in a stress situation, larger firms are more likely to fail because they need more resources to recover. Since large firms are relatively stable, their stress is also less likely to be temporary. According to the above analysis, the second hypothesis is formed as follows:

HYPOTHESIS 2. For a sample of stressed firms, firm size is positively related to the likelihood of bankruptcy.

SIZE (proxy as logarithm of total assets, logarithm of sales, etc.) is used as an important individual predictor of bankruptcy in prior research. Firms with different sizes can require different conditions (e.g., leverage level, liquidity level, earning level) for survival. Therefore, I expect that firm size impact the relation between bankruptcy and other firm characteristics. However, whether and how such relations exist has not been explored by prior studies. In this study I empirically test whether models’ prediction power will be enhanced by incorporating the impact of size upon the relation between bankruptcy and other firm characteristics. The corresponding hypothesis is as follows:

HYPOTHESIS 3. Firm size has an impact upon the relation between the likelihood of bankruptcy and other firm characteristics.

4. Research Method

4.1 Sample and Data

The data employed in estimating and testing models span the period from 1989 to 2002. This span is chosen to obtain a sizable sample while providing evidence for a recent period of bankruptcy activity. The sample is divided into a training sample and a holdout sample. The training (estimation) period covers ten years, from 1989 through 1999. The holdout period is
from 2000-2002. The following steps are used to identify bankrupt firms. First, bankrupt firms are identified through Compustat and Lexis-Nexis Bankruptcy Report databases. Next, bankruptcy filing dates are determined using the Lexis-Nexis Bankruptcy Report library, Lexis-Nexis News and firms’ Form 8-K reports. Firms without available bankruptcy filing dates are eliminated. For each bankrupt firm, the most recent Form 10-K report filed prior to its bankruptcy filing is identified. The lag between the fiscal year end of 10-K report and bankruptcy filing date must be less than 2 years. To form the sample of non-bankrupt firms, 500 active firms are randomly selected for each sample year of the study period. Form 10-K reports for the fiscal year-end one or two years prior to the sample year are used. Stock information is from the year prior to the sample year. I obtain financial information from Compustat and stock information from CRSP. Firms with incomplete information are deleted. Table 1 describes the sample selection process.

*************** Insert Table 1 here ***************

4.2 Regression Model

The dependent variable in the prediction models is each firm’s bankruptcy status (0, 1) in a given sample year. The independent variables are a set of bankruptcy predictors. Logistic regression is typically used in accounting studies with discrete dependent variables. Similarly,

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3 The bankrupt sample in this study consists of firms that file bankruptcy petitions under both Chapter 11 and Chapter 7.
4 Similar to Begley et al. (1996), I use this requirement to ensure the data used for prediction are current.
5 A firm is considered as active in a sample year if Compustat provides the closing market price for December of that year.
6 10-K report for the fiscal year-end two years prior to the sample year is used if 10-K report for the fiscal year-end one year prior to the sample year does not contain complete information.
this study uses a logistic regression method to develop models and test hypotheses. The form of
the logistic model is:

\[ Pr(Y) = \frac{1}{1 + e^{-(\alpha + \beta x)}} \]  

(1)

where \( Pr(Y) \) represent the probability of bankruptcy, \( X \) is the set of independent variables, and \( \alpha, \beta \) are unknown parameters.

To avoid oversampling bias (which is, the sample proportion of bankruptcies is higher
than the population proportion), the logit model’s intercept is adjusted for the difference between
the proportion of bankrupt firms in the study sample and that in the real world. Similar to
Hopwood et al. (1994), the following adjusted model suggested by Anderson (1972) is
employed:

\[ Pr(Y) = \frac{1}{1 + e^{-(\gamma + \alpha + \beta x)}} \]  

(2)

where: \( \gamma = \text{Ln}[\text{prop}(NB) \times \text{prop}'(B)] - \text{Ln}[\text{prop}'(NB) \times \text{prop}(B)] \)

\( \text{prop}(NB) = \text{sample proportion of nonbankrupt firms (NB)} \)

\( \text{prop}(B) = \text{sample proportion of bankrupt firms (B)} \)

\( \text{prop}'(NB) = \text{estimated population proportion of nonbankrupt firms} \)

\( \text{prop}'(B) = \text{estimated population proportion of bankrupt firms} \)

In order for the models to predict whether or not a firm will file as bankrupt, a cutoff
probability is needed. Following Hopwood et al. (1994), I use the formulas below to calculate
the cutoff: \( \text{Cutoff} = \frac{1}{1 + \text{misclassification cost ratio}} = \frac{1}{1 + \frac{C(NB|B)}{C(B|NB)}} \)  

(3)

where \( C(NB|B) \) represents the cost for misclassifying a bankrupt firm as nonbankrupt,
\( C(B|NB) \) represents the cost for misclassifying a nonbankrupt firm as bankrupt.

The prediction power of a logistic regression in the holdout sample is measured using Estimated Misclassification Cost (EMC), calculated as follows:

\[
EMC = C(NB|B) \times prop'(B) \times P(NB|B) + C(B|NB) \times prop'(NB) \times P(B|NB),
\]

(4)

where \( P(NB|B) \) represents the probability that a prediction model misclassifies a bankrupt firm as nonbankrupt, calculated as the number of bankrupt firms misclassified as nonbankrupt divided by the total number of bankrupt firms in the holdout sample,

\( P(B|NB) \) represents the probability that a prediction model misclassifies a nonbankrupt firm as bankrupt, calculated as the number of nonbankrupt firms misclassified as bankrupt divided by the total number of nonbankrupt firms in the holdout sample,

\( C(NB|B) \), \( C(B|NB) \), \( prop'(NB) \), \( prop'(B) \) are defined same as above.

The advantage of EMC is that it takes into consideration the population proportion of bankrupt firms and the relative costs of Type I error and Type II error. There are no theoretical distributions existing for describing EMC. Bootstrapping is used to estimate the empirical distributions of EMC and to determine the critical values for hypotheses testing. The analysis of EMCs will be conducted under various misclassification cost ratios ranging from 1:1 to 100:1 \((C(NB|B) : C(B|NB))\).

### 4.3 The Development of a Base Bankruptcy Prediction Model

A base bankruptcy prediction model is needed for testing hypotheses. Eight variables including seven financial ratios from Hopwood et al. (1994) and an auditor opinion variable are used to develop the base model. Hopwood et al. (1989) show that the consistency exception and the going-concern qualification have incremental explanatory power beyond financial ratios in a
bankruptcy-prediction model. Therefore, I incorporate the auditor opinion variable into the model. Table 2 provides definitions of variables.

4.4 Definition of Stress Criteria

The variable, STRESS, is set to ‘one’ if a firm is defined as stressed, otherwise ‘zero’. Four Stress Criteria are compared in this study. Table 3 provides a detailed description of each criterion. Table 4 lists the number of stressed firms and nonstressed firms under each criterion in both the training and test sample.

5. Empirical Results

Similar to Hopwood et al. (1994), two procedures are conducted to test hypothesis 1. The first procedure is to compare the goodness-of-fit of models defined under different stress criteria. The second procedure is to compare these models’ performance in the holdout sample.

The base model developed in Section 4 is called Model 0 for the following discussion. First, I add STRESS as an individual variable to the base model to form Models 1.1, 2.1, 3.1, and 4.1, respectively under Criterion 1. Auditor View Criterion, 2. Altman Z-score, Criterion 3. Zmijewski Probability, and Criterion 4. Stock Return. Next, both STRESS and the interactions between STRESS and the eight control variables are added to the base model. Thus, Models 1.2,

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7 The results of the second procedure are not available for this version of the paper.
2.2, 3.2, and 4.2 are constructed under each of the four criteria. For the following discussion, Models 1.1, 2.1, 3.1, and 4.1 are called stress models, and Models 1.2, 2.2, 3.2, and 4.2 are called stress interaction models. Models under each criterion are trained using both the maximum training sample and the common training sample. The maximum training sample under one stress criterion consists of all firms that possess complete information under the criterion, and the common training sample consists of firms with complete information under all criteria. For each of the four stress models and four stress interaction models, the incremental Chi-square ($\chi^2$) beyond Model 0 is calculated and its significance is tested. The comparison of fitting levels among models is provided in Table 5.1 and Table 5.2. Models in Table 5.1 are developed using the maximum training samples. Models in Table 5.2 are developed using the common training sample.

Using training period data, I first analyze the incremental power of four stress models and four stress interaction models beyond the base model, Model 0. Results from both table 5.1 and table 5.2 suggest that, compared to Model 0, all four stress models (Models 1.1, 2.1, 3.1, 4.1) have a significant incremental $\chi^2$ statistics (1 degree of freedom) significant at a $p < 0.01$ level based upon one-tailed test. Compared to Model 0, all four stress interaction models (Models 1.2, 2.2, 3.2, 4.2) have incremental $\chi^2$ statistics (8 degrees of freedom) significant at a $p < 0.01$ level based upon one-tailed test. However, there are large differences among models’ fitting levels under different stress criteria. Models with stress defined under the Zmijewski Probability Criterion and the Stock Return Criterion have much higher fitting levels than the Auditor View Criterion and the Altman Z-score Criterion. For instance, as suggested in Table 5.2 in which
models are estimated using the common training sample, stress models 3.1 and 4.1 respectively have an incremental $\chi^2$ of 391.482 and 464.288 beyond Model 0, while stress models 1.1 and 2.1 respectively have an incremental $\chi^2$ of 380.489 and 354.264. Stress interaction models 3.2 and 4.2 respectively have an incremental $\chi^2$ of 439.903 and 501.859 beyond Model 0, while stress interaction models 1.2 and 2.2 respectively have an incremental $\chi^2$ of 397.428 and 366.782. Therefore, I conclude that the null Hypothesis 1 is rejected. There is significant difference among the four stress criteria studied regarding their effectiveness as sample partitioning tools.

Next, I discuss the incremental power of stress interaction terms beyond control variables and STRESS variable. This incremental power is reflected by the differences in $\chi^2$ statistics between stress interaction models and stress models under the same criteria. According to Table 5.1 and 5.2, except for the interaction model estimated using the common sample under the Altman Z-score criterion, all other stress interaction model have a significant incremental $\chi^2$ statistic beyond the corresponding stress models. However, under all four criteria, the incremental explanatory power of stress interaction models above stress models is much less than the incremental power of stress model beyond Model 0, especially taking into account the number of freedoms. For instance, under the Stock Return Criterion and estimated using the common sample, the stress model (Model 4.1) has an incremental $\chi^2$ of 174.776 with only 1 degree of freedom, beyond Model 0, while the stress interaction model (Model 4.2) has an incremental $\chi^2$ of 37.571 with nine degree of freedom, beyond Model 0. This indicates that to simply re-estimate the coefficients of the same variables using partitioned samples is far from enough; different sets of variables might be needed for samples with different stress level.
Since each stress criterion contains certain unique noises in measuring firms’ stress level, it is reasonable to believe that a combination of more than one stress criterion can reduce the noises and therefore better represent stress levels. In order to test this expectation, I create a new criterion, which is a combination of the Zmijewski Probability Criterion and the Stock Return Criterion, which are two better-performing criteria shown earlier. The new combined criterion is defined as ‘one’ if a firm is defined as stressed by both criteria, otherwise ‘zero’. Table 6 reports the comparison of fitting levels between models under this new combined criterion and the base model, Model 0.

Table 6 reports the comparison of fitting levels between models under this new combined criterion and the base model, Model 0.

The results in table 6 show that the new combined criterion is more effective than each individual criterion. For instance, estimated using the common sample, the stress model under the new combined criterion has an incremental $\chi^2$ of 201.789, compared to 101.97 under the Zmijewski Criterion and 174.776 under the Stock Return Criterion; the stress interaction model under the new combined criterion has an incremental $\chi^2$ of 252.369, compared to 150.391 under the Zmijewski Criterion and 212.347 under the Stock Return Criterion.

Hypothesis 2 asserts a positive relation between client size and the probability of bankruptcy for stressed firms. Since the purpose of this hypothesis is not for prediction but to test a relationship, I test it using the entire sample including training and test samples. I partition the sample based upon four different stress criteria and estimate models separately for stressed samples and nonstressed samples. To ensure that the obtained results are not biased by the proxy used for client size, I test the hypothesis using two different proxies of client size, sales proxy (calculated as logarithm of total sales) and assets proxy (calculated as logarithm of total sales).
Table 7 Panel A reports the coefficient information for the size variable in the different models when sales proxy is used to measure client size, while table 7 Panel B provides the coefficient information for the size variable measured by assets proxy. As shown in Panel A, regardless of the stress criterion used, sales proxy has a negative and highly significant coefficient when models are estimated using the stress sample. Panel B suggests, the hypothesized negative relation between client size and probability of bankruptcy still exists when client sized is measured by total assets, although in a weaker manner. Specifically, the coefficient for assets proxy is positive under all four stress criteria, being significant at \( p < 0.05 \) level under two stress criteria and being insignificant under the other two criteria. Overall, Hypothesis 2 is accepted. Note that in nonstressed samples, sales proxy does not show a consistent sign across different criteria, while assets proxy consistently shows a negative sign. Further research is needed to better understand the relation between the size of an unstressed client and its probability of bankruptcy.

To test hypothesis 3, an interaction model is formed by adding to the base model interaction terms between size variable and other control variables. This interaction model is estimated using the full training sample and tested using the full test sample. Its model fitting level in the training sample and prediction performance in the test sample\(^8\) are compared with those of the base model. Again, I test the hypothesis using two different size proxies, sales proxy and assets proxy. Table 8 provides the comparison of fitting levels between Model 0 and the models with size interaction terms. Regardless of the size proxy used, most interaction terms are

\(^8\) Performance in the test sample is not available for this version of the paper.
significant at a p<0.01 level based upon a two-tailed test. Compared to the base model’s Chi-square, the Chi-square of the interaction model using the sales (assets) proxy is 286.563 (332.854) higher, with 7 degrees of freedom, statistically significant at a p < 0.1% level. Therefore, Hypothesis 3 is accepted.

6. Conclusion

In this study I analyze the effects of firm stress level and size on the performance of bankruptcy prediction models. First, four different stress criteria are tested regarding their effectiveness in increasing bankruptcy prediction models’ power. These four criteria are: 1. Auditor View Criterion, 2. Altman Z-score Criterion, 3. Zmijewski Probability Criterion, 4. Stock Return Criterion. My analysis results show that, as suggested by Hopwood et al. (1994), firm stress level does have an incremental explanatory power and therefore increase the performance of bankruptcy prediction models. Among the four criteria tested, the Auditor View Criterion and the Altman Z-score Criterion are less effective than the Zmijewski Probability Criterion and the Stock Return Criterion. I also find that, the interaction terms between stress level and other predictors add a much lower incremental power than simply a stress level variable. This suggests that to simply re-estimate the coefficients of the same variables using partitioned samples is far from enough; different sets of variables could be needed for samples with different stress level.

Secondly, I hypothesize and find a positive relationship between firm size and the probability of bankruptcy for stressed firms. This is contradictory to prior studies’ (e.g. Ohlson 1980) conclusions, which suggest that larger firms are generally less likely to go bankrupt. The
following reasoning is provided to support the finding. Because large firms are more stable, their stress is less likely to be temporary. Large firms usually are well operated and have more resources, so they do not encounter a stress situation as easily as small firms. Once they do face stress, this may indicate a more serious problem. In addition, it is more difficult for large firms to recover from stress because the recovering requires more resources. In addition, this study does not find a consistent relation between the size of an unstressed client and the probability of bankruptcy. Further research is desired to better understand this relationship.

Third, past research usually employs firm size as an individual predictor, ignoring its impact upon the relation between bankruptcy and other predictors. Since firms with different sizes can require different conditions (for instance, different leverage, different level of working capital, different earning ability) for survival, I hypothesize that firm size has a significant impact upon the relationship between the probability of bankruptcy and other bankruptcy predictors. This hypothesis is supported. The interaction terms between firm size and other predictors have added significant incremental explanatory power to bankruptcy prediction models.
REFERENCES


Table 1 Sample Selection

**Bankruptcy Sample**

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<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
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<tr>
<td>1</td>
<td>Bankrupt firms identified from Lexis-Nexis Bankruptcy Report Database</td>
<td>974</td>
</tr>
<tr>
<td></td>
<td>Minus: bankrupt firms not included in Compustat</td>
<td>134</td>
</tr>
<tr>
<td></td>
<td>Subtotal</td>
<td>840</td>
</tr>
<tr>
<td>2</td>
<td>Bankrupt firms identified from Compustat</td>
<td>413</td>
</tr>
<tr>
<td></td>
<td>Minus: bankrupt firms that do not have bankruptcy filing dates identified</td>
<td>124</td>
</tr>
<tr>
<td></td>
<td>Minus: bankruptcy filing dates are not in the period of 1989-2002</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>Subtotal</td>
<td>270</td>
</tr>
<tr>
<td>3</td>
<td>Total number of bankrupt firms from both sources with bankruptcy filing dates between 1989-2002</td>
<td>1110</td>
</tr>
<tr>
<td></td>
<td>Minus: bankrupt firms that do not have such a 10-K filed prior to bankruptcy that the lag between the fiscal year end of the 10-K and the bankruptcy filing date is within two years</td>
<td>220</td>
</tr>
<tr>
<td></td>
<td>Subtotal</td>
<td>890</td>
</tr>
</tbody>
</table>

*Step 1-3 are the same under all criteria*

**Bankruptcy sample under Criterion 1: Auditor View**

<table>
<thead>
<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>Minus: firms with incomplete information under Criterion 1</td>
<td>177</td>
</tr>
<tr>
<td></td>
<td>The final bankruptcy sample under Criterion 1</td>
<td>713</td>
</tr>
</tbody>
</table>

**Bankruptcy sample under Criterion 2: Altman Zscore**

<table>
<thead>
<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>Minus: firms with incomplete information under Criterion 2</td>
<td>118</td>
</tr>
<tr>
<td></td>
<td>The final bankruptcy sample under Criterion 2</td>
<td>772</td>
</tr>
</tbody>
</table>

**Bankruptcy sample under Criterion 3: Zmijewski Probability**

<table>
<thead>
<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>Minus: firms with incomplete information under Criterion 3</td>
<td>112</td>
</tr>
<tr>
<td></td>
<td>The final bankruptcy sample under Criterion 3</td>
<td>778</td>
</tr>
</tbody>
</table>

**Bankruptcy sample under Criterion 4: Stock Return**

<table>
<thead>
<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>Minus: firms with incomplete information under Criterion 4</td>
<td>293</td>
</tr>
<tr>
<td></td>
<td>The final bankruptcy sample under Criterion 4</td>
<td>597</td>
</tr>
</tbody>
</table>

**Nonbankrupt sample**

<table>
<thead>
<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>500 active firms randomly selected for each sample year during 1989-2002</td>
<td>7000</td>
</tr>
<tr>
<td></td>
<td>(Step 1 is the same for all criteria)</td>
<td></td>
</tr>
</tbody>
</table>

**Nonbankruptcy sample under Criterion 1: Auditor View**

<table>
<thead>
<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Minus: Firms that do not have complete information under Criterion 1</td>
<td>3282</td>
</tr>
<tr>
<td></td>
<td>The final nonbankrupt sample under Criterion 1</td>
<td>3718</td>
</tr>
</tbody>
</table>

**Nonbankruptcy sample under Criterion 2: Altman Zscore**

<table>
<thead>
<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Minus: Firms that do not have complete information under Criterion 2</td>
<td>2361</td>
</tr>
<tr>
<td></td>
<td>The final nonbankrupt sample under Criterion 2</td>
<td>4639</td>
</tr>
</tbody>
</table>

**Nonbankruptcy sample under Criterion 3: Zmijewski Probability**

<table>
<thead>
<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Minus: Firms that do not have complete information under Criterion 3</td>
<td>2283</td>
</tr>
<tr>
<td></td>
<td>The final nonbankrupt sample under Criterion 3</td>
<td>4717</td>
</tr>
</tbody>
</table>

**Nonbankruptcy sample under Criterion 4: Stock Return**

<table>
<thead>
<tr>
<th>Step</th>
<th>Condition</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Minus: Firms that do not have complete information under Criterion 4</td>
<td>3486</td>
</tr>
<tr>
<td></td>
<td>The final nonbankrupt sample under Criterion 4</td>
<td>3514</td>
</tr>
</tbody>
</table>

Bankrupt firms with complete information under all stress criteria | 565
Nonbankrupt firms with complete information under all stress criteria | 3289