Financial Decisions, Summer 2009, Article 5

VaR as a Determinant of Capital Structure and Bankruptcy Prediction

Stephen Huffman and Michael Schellenger
University of Wisconsin Oshkosh

Abstract

We examine the ability of Value-at-Risk (VaR) to explain the future capital structure of firms that filed for bankruptcy from 1990 through 2004 and a matched sample of non-bankrupt firms. We test the proposition that VaR has an impact on a firm's probability of bankruptcy, which then can be used to explain future levels of debt. In addition to finding that VaR is significantly related to predicting the bankruptcy event, we find that the lagged probability of bankruptcy estimates using traditional variables and VaR are significantly related to the level of debt used by both the bankrupt firms and the matched firms. Further, we find that our VaR measure is related to the level of future debt used by firms in a single-variable regression model. Therefore, we find evidence that is consistent with traditional capital structure theory, which suggests that capital structure is a function of the expected cost of bankruptcy.

VaR as a Determinant of Capital Structure and Bankruptcy Prediction

1. Introduction

We examine the ability of Value-at-Risk (VaR) to explain the future capital structure of the firms in a sample of bankrupt and non-bankrupt firms. Traditional capital structure theory, developed by Modigliani and Miller (1963), suggests that a firm's capital structure is determined by a trade-off between the tax benefits of debt and the expected bankruptcy cost of debt. In contrast to previous studies that indirectly measure the expected cost of bankruptcy, we use a probability of bankruptcy from a bankruptcy prediction model to directly estimate the cost of bankruptcy. Furthermore, we investigate the proposition that VaR is a determinant of the market's perception of a firm's probability of bankruptcy and that lagged VaR measures can explain the debt levels of bankrupt and non-bankrupt firms.

Empirical tests of the trade-off theory find that firms have debt ratios that are substantially below what the level of the tax benefits of debt would support (Miller, 1977), which suggests that factors, like expected bankruptcy cost, may offset the tax advantage of debt financing. Researchers provided alternative explanations for capital structure (e.g., agency theory, Jensen and Meckling (1976) and asymmetric information, Myers and Majluf (1984)). However, Ju, Parrino, Poteshman, and Weisbach (2005) suggest that prior empirical studies may not have properly estimated expected bankruptcy cost. Studies that use firm attributes (Titman and Wessels, 1988; Hovakimian, Opler, and Titman, 2001) such as asset structure, growth, uniqueness, size, earnings volatility, and profitability may have underestimated the expected bankruptcy cost.

In the trade-off theory, expected bankruptcy cost is defined as the product of the probability of bankruptcy and the total dollar cost of bankruptcy. Assuming the dollar cost of bankruptcy is constant, the expected bankruptcy cost varies with the probability of bankruptcy. Prior empirical investigations of capital structure indirectly estimate the probability of bankruptcy using firm attribute measures to estimate risk. These studies assume that greater firm attribute risk implies greater probability of bankruptcy. However, empirical tests of the trade-off theory of capital structure do not have to use firm attribute risk to indirectly proxy the probability of bankruptcy. Traditional bankruptcy models provide a direct estimate of the probability of bankruptcy.

Numerous studies have addressed whether statistical models can be used to estimate a firm's probability of bankruptcy and if that probability can be used to predict which firms actually will fail. Early bankruptcy studies (Altman, 1968; Beaver, 1968) relied upon accounting-based variables to estimate a probability of bankruptcy and to predict bankruptcy. Financial ratios used in these models proxy various types of risk such as business risk, liquidity risk, and financing risk. Other bankruptcy studies assume the risk and value of the firm is a function of the firm's cash flow. These models (Gentry Newbold and Whittford, 1985; Aziz, Emanual and Lawson, 1988) develop cash flow measures to proxy the risk of insufficient cash flow to service existing debt or to attract additional external financing.

Although the Altman Z Model (Altman, 1968) has been a standard bankruptcy model over time, Mossman, Bell, Swartz, and Turtle (1998) conclude that neither the Altman Z Model nor a cash flow model (Aziz et.al., 1988) is entirely satisfactory in classifying and predicting bankrupt and non-bankrupt firms. Although bankruptcy models provide an estimate of the probability of bankruptcy, the accounting-based models still may be missing an important measure of bankruptcy risk.

Recent evidence suggests that market-based variables have more explanatory power than accounting or cash flow variables in explaining bankruptcy (Shumway, 2001; Hillegeist, Keating, Cram, and Lundstedt, 2004; Chava and Jarrow, 2004; Beaver, McNichols, and Rhie, 2005). Market volatility is crucial because it captures the probability that the market value of the assets will decline to an extent that the value of assets is insufficient to cover the firm's debts. However, bankruptcy is an asymmetrical event, and previous market-based bankruptcy studies measure volatility with symmetrical variables such as standard deviation of returns.

Our analysis of the trade-off theory of capital structure differs from prior research in a number of respects. First, we use a direct estimate of the probability of bankruptcy, rather than an indirect estimate, to explain a firm's future debt ratio. Second, we evaluate the impact of including a market-based asymmetric variable, Value-at-Risk, with traditional bankruptcy variables on: (1) the probability of bankruptcy, and (2) the future debt ratio of individual firms. Finally, we evaluate if our market-based asymmetric measure, VaR, can explain a firm's future debt ratio.

Motivated by the lack of direct tests of the cost of bankruptcy and the increased popularity of downside risk measures like VaR, we estimate the probability of bankruptcy for firms that filed for bankruptcy from 1990 through 2004 and a matched sample of non-bankrupt firms using logistic regression. We use a five-variable traditional model based on the Altman (1968) model and then include our measure of VaR in the model. We find that our VaR measure is significant in the logistic regression models estimated two years prior to the bankruptcy filing. When we use these probability estimates of bankruptcy, made two years prior to the bankruptcy filing, in OLS regression models to explain debt ratios one year prior to bankruptcy, we find that they are significant. We also find that the lagged probability of bankruptcy estimates are significantly related to the debt ratios of firms in the non-bankrupt sample. Therefore, we find evidence that is consistent with traditional capital structure theory, which suggests that capital structure is a function of expected bankruptcy costs. Further, we find evidence that VaR can be used in bankruptcy prediction models and that this market-based downside risk measure can be used to predict future debt ratios.

In the next section, we explain why we include a measure of VaR with a traditional bankruptcy model. In the third and fourth sections, we describe our methodology and data sample. Sections five and six contain our empirical results and conclusions.

2. Background

If, as Stulz (1996) contends, the firm's cash flow and the variability of that cash flow are unsystematic, then managing specific attributes of the firm or specific types of risk such as business risk, asset risk, or financial risk, will have little or no impact on the firm's probability of bankruptcy. Unsystematic cash flow is irrelevant to shareholders with well-diversified portfolios. Consequently, Stulz argues that increases in specific types of risk e.g., business risk, may not necessarily increase the probability of bankruptcy. If the risk of the firm increases, but the probability of bankruptcy does not increase, then the value of the firm is not affected. On the other hand, an increase in risk that increases the probability of incurring bankruptcy costs is harmful because it reduces the value of the firm.

The risks that increase the probability of bankruptcy are risks that create large losses. Large losses, like bankruptcy and financial distress, occur in the extreme left tail of a distribution. The probability of bankruptcy, and hence the value of the firm, is affected not only by risk associated with a symmetrical distribution, but also by risk measures that capture the likelihood of large, but infrequent, negative returns. That is, we suggest that bankruptcy models need to include a measure of the risk that imposes large costs upon the firm.

VaR is a statistical measure of downside risk that has been developed in the financial institutions arena to evaluate portfolio risk (Jorion, 2001). VaR is a measurement of the largest expected loss given a specific time horizon and a degree of confidence. As such, VaR is a measure of the firm's worst possible outcome, over a given time horizon with a specified degree of confidence. VaR measures the worst case scenario, and bankruptcy is the worst case scenario for a firm. For that reason, we investigate the relationship between VaR and the probability of bankruptcy. Further, if VaR is related to the probability of bankruptcy and capital structure is related to the probability of bankruptcy, then we postulate that VaR should be related to capital structure.

3. Methodology and Model Development

Our investigation of the relationship between VaR and capital structure is conducted within the context of a traditional bankruptcy model, the Altman Z Model (1968).[1] Our version of the Altman model is presented below:

$$\text{Probability of Bankruptcy} = f\begin{pmatrix} \dfrac{Working\ Capital}{Total\ Assets}, \dfrac{Retained\ Earnings}{Total\ Assets}, \dfrac{EBIT}{Total\ Assets}, \\ \dfrac{Sales}{Total\ Assets}, \dfrac{Market\,Value\ of\ Equity}{Book\ Value\ of\ Total\ Liabilities} \end{pmatrix} \quad (1)$$

Specification of the model and the variables used are found in the Appendix, along with variable definitions and mnemonics as extracted from Standard and Poor's Compustat database. We refer to the model from equation (1) as Model ALT, and when we add our measure of VaR to the equation as Model ALTVaR. We add a number after the model name to indicate the number of annual periods prior to the bankruptcy filing.

Our measure of VaR is a historical measure that is calculated as the lowest market-adjusted return over the 12 months ending with the fiscal year-end month and is calculated for each of

[1] We use the same ratios as those used by Altman (1968), with one exception. Whereas Altman uses market value of equity to long-term debt, we use market value of equity to total liabilities. The use of total liabilities maintains our sample size. When we conduct the analysis with the exact Altman model, we arrive at similar results, and therefore the same conclusions.

the two time lags.[2] For example, if a firm with a fiscal year-end of December files for bankruptcy in August 2003, the t−1 year would include the 12 months ending in December 2002, and the t−2 calculations would be from the 12 months ending in December 2001. Each monthly stock return is market-adjusted by subtracting the associated monthly return on the S&P 500 Index to create the variable, VaR. Larger (smaller) negative values for our measure of VaR indicate greater (less) risk.

Our analysis is focused on the two years prior to bankruptcy, years t−1 and t−2, because: (1) We use an estimate of the probability of bankruptcy and VaR to predict a future capital structure. That is, we use our estimate of the probability of bankruptcy and our measure of VaR in time period t−2 to explain future capital structure in time period t−1. (2) We are not concerned with earlier time periods because as Mossman *et al*. (1998) conclude, "bankruptcy models do not perform particularly well more than two years prior to bankruptcy (pg 45)." Most recent bankruptcy studies are based on time period t-1 only (Beaver *et al*., 2005; Chava and Jarrow, 2004; Hillegeist *et al*., 2004; Shumway, 2001). Although not presented here, our analysis of the time period t-3 probability of bankruptcy is consistent with the Mossman conclusion.

4. Data

The initial sample is comprised of all U.S. firms that filed for bankruptcy in the years 1990-2004. The list of bankrupt firms is derived from BankruptcyData.com. We excluded all financial institutions (SIC code 6000) and ADRs from the bankrupt firm sample. The bankruptcy filing date is the date listed by BankruptcyData.Com. Consistent with Mossman *et al*. (1998), we set the condition that the most recent fiscal year prior to bankruptcy must end at least six months prior to the date of bankruptcy. As illustrated in Figure 1, we refer to that fiscal year as year t−1, i.e., the one year prior to bankruptcy. We refer to data for two years prior to bankruptcy as fiscal year t−2. To be included in the final bankrupt sample, complete data for the three years prior to the bankruptcy year must be available. Of the original sample, 254 bankrupt firms remain in the final sample. The mean time from the bankruptcy filing month to the date of the financial statements is 12.6 months, with a minimum of 7 months and a maximum of 18 months.

We match each of the 254 bankrupt firms with a non-bankrupt firm on the basis of industry and size.[3] We begin with a listing of non-bankrupt firms with the same four-digit SIC code. From this listing, we select a firm of similar size, where size is proxied by book value of total assets. In a number of instances, using a four-digit SIC code does not yield a similar size firm. In

[2] We also conduct our analysis using a VaR measure that did not adjust for market returns, and find similar results that do not alter our primary conclusions.

[3] The use of the matched sample allows us to specifically control for firm size and industry, which is somewhat more realistic. For example, a sector analyst evaluating firms in a section in order to make a buy or sell recommendation is most likely to compare peer group firms.

those instances, we use a two-digit SIC code to define industry.[4] We also require that each matched firm has complete data for the three years prior to the associated bankrupt firm's bankruptcy date. All financial statements and return data required for the 508 firms in the study are obtained from Standard and Poor's Compustat data base.

5. Results

In the initial step of our analysis, we confirm the relationship between the debt ratio, DAT, and our measure of VaR. A comparison of the debt ratios between our sample bankrupt and non-bankrupt firms indicates that significant differences exist. In Table 1, we present summary statistics on the variables used in our models. In columns two and three, we report the correlation coefficients between DAT in time period t−1 and the variables used in our models for the time periods t−1, t−2, and t−3. As postulated, our measures of VaR, for all time periods, are negatively correlated with DAT in period t−1.[5] The mean values for DAT and VaR for bankrupt and non-bankrupt firms are significantly different for all three time periods prior to the bankruptcy date, which is not the case for all the Altman model variables used in the analysis. For example, there is a significant difference, at the five percent level, between the bankrupt and the non-bankrupt firms' working capital ratio, WCAT, in the period prior to the bankruptcy filing, but not in the t−2 or t−3 periods. Although the univariate analysis is interesting, because of the complexities of the bankruptcy event, most empirical studies since Beaver (1968) have used multivariate models.

In Table 2, we report the logistic regression model results for the full sample of bankrupt and non-bankrupt firms for all versions of our model. For each of the models with the traditional five variables, models ALT1 and ALT2, the likelihood ratio is significant at less than the one percent level; however, none of the traditional variables are consistently significant, at the five percent level, over the two time periods. EBITAT and WCAT are significant, at the five percent level, in time period t−1. When we add our VaR variable to the variables in the traditional model (models ALTVaR1 and ALTVaR2), we find that VaR is of the anticipated sign and is significant at the one percent level in both models (i.e., both time periods). For both time periods, the traditional model with the inclusion of our measure of VaR produces a higher pseudo-r-square and likelihood ratio.[6]

---

[4] A paired comparison test of means differences failed to find a significant difference between the bankrupt firms and the non-bankrupt firms' size (market value of equity) or ratio of book value-to-market value, at the five percent level of significance. Therefore, our matching process was effective.

[5] The values for the Pearson correlation coefficients between the DAT_{t-1} variable and the VaR measures for each time period are all significantly different from zero at the one percent level.

[6] We also analyze a logit model using the Aziz *et al.* (1988) cash flow variables. Similar to the traditional models reported in Table 1, when VaR is added to the Cash Flow models, VaR is significantly negative in period t−1 and period t−2 with the anticipated sign. The Cash Flow models with VaR produce higher values for r-square and the likelihood ratio for both time periods. Thus, our VaR is significant in alternative bankruptcy models using logistic regression.

These results support our contention that VaR improves the performance of our bankruptcy model. For the traditional model, our logit results indicate that VaR does increase the explanatory power. Additionally, as we report the rows near the bottom of Table 2, when VaR is included in the traditional model, the correct classification rates improve. This is particularly true for the t−2 model. Our results also are consistent with previous bankruptcy research in that earlier classification of bankruptcy (t−2) is more difficult than later classification (t−1). Therefore, in Table 2, we show that our measure of VaR improves the traditional bankruptcy model in terms of explaining the bankruptcy event and classifying firms that later file for bankruptcy.

The second step of our analysis is to use the time period t−2 estimates of the probability of bankruptcy from the logit models in an OLS model to determine whether these probabilities can explain capital structures in time period t−1. For this analysis, we define capital structure as total debt in time period t−1 divided by book value of total assets at t−1, as shown in equation (2):

$$DAT_{t-1} = \frac{Total\ Debt_{t-1}}{Book\ Value\ of\ Total\ Asset_{t-1}}. \qquad (2)$$

We continue our analysis by partitioning the full sample of 508 firms into five quintiles based on our market-adjusted VaR for the time period t−2. In Panel A of Table 3, we report results of partitioning the quintiles by their bankrupt/non-bankrupt status. For both the bankrupt and the non-bankrupt samples, quintile one represents the firms with the most negative values for VaR; i.e., the firms with the most downside risk. We find that almost two-thirds of the firms in the lowest VaR quintile are from the bankrupt sample, and over 70 percent of the firms in the highest VaR quintile are from the non-bankrupt sample.[7] Thus, when using VaR_{t-2}, there appears to be a relationship between VaR and bankruptcy.[8]

Also in Panel A of Table 3, we present the mean values for VaR and DAT for three lagged time periods for each of the quintiles formed using VaR_{t-2}. As expected, we report that for the bankrupt firm sample, the mean value of VaR decreases (becomes more negative) from t−3 to t−1. A test of mean differences between VaR_{t-1} and VaR_{t-3} confirms that there is a significant statistical difference in VaR for the bankrupt firms, across all VaR quintiles (at the 10 percent level of significance). We find similar results for the differences in VaR for t−2 and t−1.[9] For

[7] A binominal test of proportions for these quintiles indicates that the reported proportions are significantly different for both samples, at the one percent level, than what would be expected if the firms were randomly selected into the quintiles.

[8] Although not reported in Table 3, when we partition the sample by $VaR_{t-3,}$ we find that 58.4 percent of the firms in the lowest VaR quintile are from the bankrupt sample and 62.7 percent of the firms in the highest VaR quintile are from the non-bankrupt sample, which also supports our assertion of a relationship between VaR and bankruptcy.

[9] The mean values for VaR in quintile one actually increase between two years prior to bankruptcy and one year prior to bankruptcy. When we evaluate the median values we find that the median VaR_{t-1} is −39.13 percent, compared to −45.14 percent for VaR t−2. A Wilcoxon signed rank confirms that the results for the mean differences produce similar conclusions for both the bankrupt and the non-bankrupt samples.

non-bankrupt firms, a test of mean difference for all 254 non-bankrupt firms indicates that there is not a statistical difference in the means of VaR_{t-1} and VaR_{t-3}.

In Panel A of Table 3, we also show the relationship between VaR quintiles and the debt ratio, DAT. Across all quintiles formed using VaR_{t-2}, the mean values for DAT increase for bankrupt firms from period t−3 to period t−1. Our tests of mean differences indicate that the increase in debt ratio is statistically significant for all quintiles of bankrupt firms, at the one percent level. We find similar results for the mean differences between t−2 and t−1, with the exception of quintile one.[10] Our results indicate that bankrupt firms in our sample increase their usage of financial leverage from relatively high levels to even higher levels in the year prior to bankruptcy. In contrast, debt ratios for non-bankrupt firms hold relatively steady, as shown by the lack of statistical significance between the mean differences between periods t−2 and t−1 across the five quintiles, at the 5 percent level of significance.[11] Therefore, the bankrupt firms and the matched non-bankrupt firms appear to have significantly different capital structures; this difference becomes even more pronounced as bankruptcy becomes more imminent and more pronounced with differences in our VaR measure.

We extend our analysis of VaR qunitiles from univariate differences across time to differences in the outcomes of our multivariate model outcomes. Specifically, we find that the traditional bankruptcy model, which includes our measure of VaR, produces a probability of bankruptcy that is significantly lower for non-bankrupt firms and significantly higher for bankrupt firms (39.14 percent and 60.86 percent for the t−1 model, respectively) compared to the five variables in the traditional model (41.91 percent and 58.09 percent for the t−1 model, respectively).[12]

In Panel B of Table 3, we present the mean values for the estimated probability of bankruptcy, Phat, from the logistic regression equations for each of the quintiles formed by VaR_{t-2}, which then is partitioned further by bankrupt and non-bankrupt firms. Also in Panel B of Table 3, we provide a comparison of the estimates of bankruptcy between the models with the VaR measure (ALTVaR) and those without (ALT). Specifically, for the bankrupt firms, we find that the estimates for the probability of bankruptcy in the t−2 model are significantly higher in the lowest VaR_{t-2} quintile (69.35 percent compared to 58.17 percent), and for the non-bankrupt firms, we find significantly lower probability estimates for the highest VaR_{t-2} quintile for the models included in our VaR measure (36.02 percent compared to 44.97 percent). Therefore, in

[10] When we expand the analysis to three years prior to the bankruptcy and test the mean difference in the debt ratio from t−3 and t−1 using the quintiles formed by VaR_{t-3},we find similar results that debt ratios are increasing for the firms in the bankrupt sample.

[11] An examination of the median debt ratios using the Wilcoxon signed rank test confirms that there is not a significant difference between the debt ratios from period t−2 and period t−1 for the firms in the non-bankrupt sample, at the 5 percent level of significance.

[12] In tests of mean differences of the probability of bankruptcy between the ALT model and the ALTVaR model using the Phat variable from t−2, we find a mean difference that is 1.40 percent higher for the bankrupt firms and 1.38 percent lower for the non-bankrupt firms, and that the means are significantly different at the 1 percent level of significance.

Table 3, we provide descriptive data that indicates that VaR is related to capital structure (as measured by DAT) and that our lagged measure of VaR provides estimates of the probability of bankruptcy (from logit models) that is consistent with actual outcomes.

Finally, we test the proposition that VaR is directly (and indirectly through the probability of bankruptcy estimates) related to the future debt ratios of firms in our sample (both bankrupt and non-bankrupt firms). In Table 4, we show the results of our cross-sectional OLS regressions that use the estimates of the probability of bankruptcy (Phat) from the logistic bankruptcy models to explain future debt ratios. Specifically, we regress DAT_{t-1} as the dependent variable against $Phat_{t-2}$ as an independent variable along with VaR as expressed in equation (2) as:

$$\frac{TotalDebt_{t-1}}{Total\ Book\ Value\ of\ \ Assets} = \alpha_0 + \gamma_1 \Pr(Bankruptcy)_{t-2} + \gamma_2 VaR_{t-2} \qquad (3)$$

Although explaining contemporary capital structure level would be interesting, we are interested in determining if VaR can predict future levels of capital structure. Therefore, we use time period t−2 probability of bankruptcy (and VaR) to explain future capital structures at time period t−1.

Our results presented in Table 4 support our position that VaR is effective in predicting future capital structure. All four models reported are significant.[13] When VaR is the only independent variable, we find that the coefficient of VaR_{t-2} is negative, which indicates that lower values of VaR are related to higher future debt ratios. We also find that the coefficients for the probability of bankruptcy estimates from each of the logit models are significantly related to the debt ratios of the firms in our total sample. Specifically, we find the model with the highest value of explanatory power is the model with the probability estimate from the logit model with the five traditional variables and the VaR_{t-2} as a second independent variable (adjusted r-square of 0.1850).[14]

We test the robustness of our findings reported in Table 4 by partitioning the sample into bankrupt and non-bankrupt firms. In Table 5, we find that coefficients in single-variable regressions with estimates for the probability of bankruptcy from each logit model are significant for both the bankrupt firms and the non-bankrupt firms. As with the results reported in Table 4, we find that the coefficient for VaR_{t-2} is significant for both the bankrupt firms and the non-bankrupt firms. It is interesting to note that the r-square for the non-bankrupt firms is

---

[13] Although not reported in the tables, we also find similar results when we use the ratio of total liabilities to market value of equity as the dependent variable. We also find that our results do not change when the regression are conducted by year.

[14] We also estimate the OLS regression models with the same independent variables that were calculated 3 years prior to the bankruptcy filing (i.e., t−3) and find similar results. However, at t−3, we find that the r-square for the probability estimate from the logit model that included the five traditional variables and VaR_{t-3} has a higher r-square (0.0931) than the probability estimate from a model with only the five traditional variables, without VaR_{t-3} (0.0727). As expected, a model with independent variables from t−1 increases the r-square values; e.g., the r-square for the probability estimate from the logit model that included the five traditional variables and VaR_{t-1} has an r-square of 0.3042.

higher than for the bankrupt firms (0.1028 and 0.0670, respectively). Therefore, we provide evidence that our measure of VaR calculated two years prior to bankruptcy filing is directly related to the debt ratios for the combined sample of 508 firms.

6. Conclusions

We investigate the ability of a market-adjusted VaR measure to explain future levels of capital structure using a matched sample of 508 bankrupt and non-bankrupt firms. Our findings support the proposition that lagged measures of VaR have a significant impact on a firm's probability of bankruptcy, and consequently can be used to explain an individual firm's capital structure.

We employ traditional bankruptcy variables with and without a measure of VaR to estimate the probability of bankruptcy using logistic regression. We find that these lagged estimates of the probability of bankruptcy and our measure of VaR in OLS regression analysis are able to explain future debt ratios. Therefore, we find direct and indirect evidence that our measure of VaR can be used to explain future capital structures.

Further, we provide evidence that our measure of VaR improves the classification rates of the traditional bankruptcy model and that the coefficient of our measure of VaR is significant in logit models for one and two years prior to the bankruptcy date. In addition, logit models that include VaR provide lower estimates of the probability of bankruptcy for non-bankrupt firms and higher estimates of the probability of bankruptcy for bankrupt firms. Therefore, we find evidence that VaR is beneficial in estimating the cost of bankruptcy.

Our paper contributes to the capital structure and bankruptcy prediction literature by providing empirical evidence of the relationship between VaR and bankruptcy and that the Value-at-Risk measures can be used to explain future debt ratios. Hedge fund managers and credit analysts should include measures of Value-at-Risk in their analysis of firms that are in financial distress. Future research should explore applying the bankruptcy models to a larger sample of non-bankrupt firms to determine if VaR measures can explain the amount of debt used in firms' capital structure.

References

Altman, E., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance* 4, 589-609.

Altman, E. and M. Brenner, 1981, Information effects and stock market response to signs of firm deterioration, *Journal of Financial and Quantitative Analysis* 16, 35-51.

Altman, E., R. Haldeman, and P. Narayanan, 1977, Zeta analysis – a new model to identify bankruptcy risk of corporations, *Journal of Banking Finance* 1, 29-54.

Aziz, A., D. Emanuel, and G. Lawson, 1988, Bankruptcy prediction – an investigation of cash flow based models, *Journal of Management Studies* 25, 419-437.

Bali, T.G. and N. Cakici, 2004, Value at risk and expected stock returns, *Financial Analysis Journal* 60, 57-73.

Beaver, W., 1968, Market prices, financial ratios, and the prediction of failure, *Journal of Accounting Research,* 179-192.

Beaver, W., M. McNichols, and J. Rhie, 2005, Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy, *Review of Accounting Studies* 10, 93-122.

Chava, S. and R. Jarrow, 2004, Bankruptcy prediction with industry effects, *Review of Finance* 8, 537-569.

Clark, T. and M. Weinstein, 1983, The behaviour of common stock of bankrupt firms, *Journal of Finance* 38, 489-504.

Furnival, G.M. and R. W. Wilson, 1974, Regressions by leaps and bounds, *Technometrics* 16, 499-511.

Gentry, J., P. Newbold, and D. Whitford, 1985, Classifying bankrupt firms with funds flow components, *Journal of Accounting Research* 23, 146-160.

Hillegeist, S., E. Keating, D. Cram, and K. Lundstedt, 2004, Assessing the probability of bankruptcy, *Review of Accounting Research* 37, 5-34.

Hovakimian, A., T. Opler, and S. Titman, 2001, The debt-equity choice, *Journal of Financial and Quantitative Analysis* 1,1-24.

Jensen, M.C. and W. Meckling, 1976, Theory of the firm: managerial behavior, agency costs and ownership structure, *Journal of Financial Economics* 7, 305-360.

Jorion, P., 2001, *Value at Risk: The New Benchmark for Managing Financial Risk*, 2nd ed., New York: McGraw-Hill.

Ju, N., R. Parrino, A. Poteshman, and M. Weisbach, 2005, Horses and rabbits? trade-off theory and optimal capital structure, *Journal of Financial and Quantitative Analysis* 40, 259-281.

Miller, M., 1977, Debt and taxes, *Journal of Finance 32,* 261-275.

Modigliani, F. and M. Miller, 1963, Corporate income taxes and the cost of capital: A correction, *The American Economic Review* 53, 433-443.

Mossman, C. E., G. Bell, L. Swartz, and H. Turtle, 1998, An empirical comparison of bankruptcy models, *The Financial Review* 33, 35-54.

Myers S.C. and N. Majluf, 1984, Corporate finance and investment decisions when firms have information investors do not have, *Journal of Financial Economics* 13, 187-221.

Stulz, R., 1996, Rethinking risk management, *Journal of Applied Corporate Finance* 9, 8-24.

Shumway, T., 2001, Forecasting bankruptcy more accurately: A simple hazard model, *Journal of Business* 74, 101-124.

Titman, S. and R. Wessels, 1988, The determinants of capital structure choice, *The Journal of Finance*, 1,1-19.

Figure 1

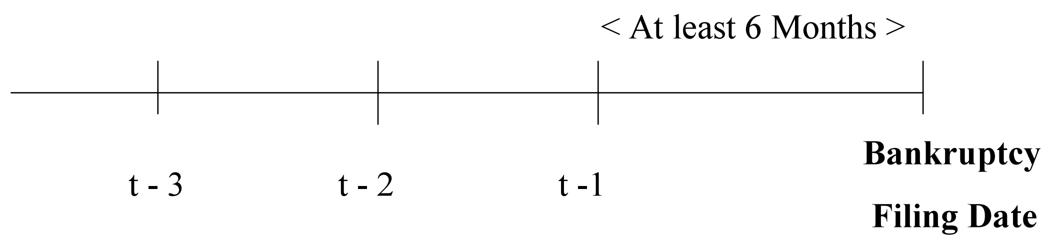

Table 1: Comparison of Variable Mean Values for Bankrupt and Non-Bankrupt Firms in the Estimation Sample 1990 to 2004

	Correlations with DAT_{t-1}		Means		Test of Differences	
Variables[a]	Bankrupt Firms	Non-Bankrupt Firms	Bankrupt Firms	Non-Bankrupt Firms	Between Means p-value for t-test	Wilcoxon Normal Approx. p-value
DAT_{t-1}	1.0000	1.0000	0.8653	0.5813	<0.0001	<0.0001
DAT_{t-2}	0.2670	0.6507	0.7948	0.5834	0.0245	<0.0001
DAT_{t-3}	0.4155	0.6085	0.6567	0.5527	<0.0001	<0.0001
VAR_{t-1}	−0.3213	−0.2914	−0.3637	−0.2467	<0.0001	<0.0001
VAR_{t-2}	−0.2589	−0.3205	−0.3066	−0.2428	<0.0001	<0.0001
VAR_{t-3}	−0.1934	−0.2914	−0.2756	−0.2415	0.0046	0.0018
$WCAT_{t-1}$	−0.7932	−0.6744	−0.0030	0.2100	<0.0001	<0.0001
$WCAT_{t-2}$	−0.4768	0.4479	0.1532	0.1999	0.1166	0.0079
$WCAT_{t-3}$	−0.2018	−0.4925	0.2020	0.2324	0.1412	0.0929
$REAT_{t-1}$	−0.4257	−0.5091	−0.8420	−0.0720	<0.0001	<0.0001
$REAT_{t-2}$	−0.1772	−0.3907	−0.6710	−0.6710	0.0625	<0.0001
$REAT_{t-3}$	−0.1670	−0.1630	−0.2130	0.0384	0.0004	<0.0001
$EBITAT_{t-1}$	−0.2677	−0.1578	−0.1180	0.0388	<0.0001	<0.0001
$EBITAT_{t-2}$	−0.2078	−0.1744	−0.0940	0.0400	0.0473	<0.0001
$EBITAT_{t-3}$	−0.1264	−0.1369	−0.0140	0.0626	<0.0001	<0.0001
TAT_{t-1}	0.1606	0.1382	1.4767	1.5516	0.3763	0.4293
TAT_{t-2}	0.0804	0.0902	1.4956	1.5582	0.6031	0.2284
TAT_{t-3}	−0.0811	0.0696	1.3767	1.5479	0.0385	0.0883
$MVLT_{t-1}$	−0.2068	−0.3766	1.3363	2.4734	0.0161	<0.0001
$MVLT_{t-2}$	−0.0697	−0.2524	2.2812	2.9165	0.4091	<0.0001
$MVLT_{t-3}$	−0.1447	−0.3386	2.8772	2.9150	0.9531	<0.0001

[a] Variables are defined as: WCAT is the ratio of working capital to total assets, REAT is the ratio of retained earnings to total assets, EBITAT is the ratio of EBIT to total assets, MVLT is the ratio of market value of equity to book value of total liabilities, and VaR is the lowest monthly market-adjusted return over the previous 12 months, which is a historical VaR and has a confidence level of 91.7 percent. DAT is the ratio of total debt to book value of assets.

Table 2: Logistic Regression Estimates for Models Using VaR and Traditional Variables
For one year prior and two years prior to the bankruptcy filing for 254 bankrupt firms and the corresponding 254 matched non-bankrupt firms in the estimation period from 1990 through 2004 (p-values for each coefficient are presented in parentheses)

Variables[a]	**One Year Prior to Bankruptcy t−1**		**Two Years Prior to Bankruptcy t−2**	
	Model ALT1 [b]	Model ALTVaR1 [b]	Model ALT2 [b]	Model ALTVaR2 [b]
Intercept	0.2148 (0.2835)	-1.1478 0.0004	0.2006 0.293	-0.6656 0.0264
WCAT	-1.6003 (0.0001)	-1.3376 0.0018	0.3858 0.3448	0.4913 0.2241
REAT	0.0449 0.7531	0.1318 0.2923	-0.3122 0.0838	-0.1891 0.2888
EBITAT	-3.9439 <.0001	-3.0705 0.0004	-1.555 0.0619	-1.1874 0.1508
TAT	0.0199 0.8534	0.0125 0.9111	-0.1605 0.1107	-0.1478 0.1454
MVLT	-0.0365 0.2005	-0.0219 0.3754	-0.0248 0.0956	-0.0192 0.1434
VaR		-0.0455 <0.0001		-0.0305 0.0002
R-squared[c]	0.1580	0.2096	0.0506	0.0778
Likelihood Ratio	87.3549 (<0.0001)	119.4747 (<0.0001)	26.3823 (<0.0001)	41.137 (<0.0001)
% Correct **Overall--** **Bankrupt--** **Nonbankrupt--**	 68.5% 69.3% 67.7%	 70.5% 69.7% 71.3%	 57.9% 57.9% 57.9%	 64.0% 63.8% 64.2%

[a] Variables are defined as: WCAT is the ratio of working capital to total assets, REAT is the ratio of retained earnings to total assets, EBITAT is the ratio of EBIT to total assets, MVLT is the ratio of market value of equity to book value of total liabilities, and VaR is the lowest monthly market-adjusted return over the previous 12 months, which is a historical VaR and has a confidence level of 91.7 percent.

[b] The number following the model letter is the number of annual periods prior to the bankruptcy filing.

[c] The r-square for logistic regression is an indicator of the predictive power of the model, also known as a pseudo-R^2 or the likelihood ratio index, and measures the percent of the uncertainty in the data explained by the model.

Table 3 Panel A: Mean Value-at-Risk and Debt-Ratio Variables Across Quintiles Determined by VaR_{t-2} and Partitioned by Bankruptcy Status

	Bankrupt Firms					Non-Bankrupt Firms				
Variables[a]	**VaR_{t-2} [a] Quintile 1**	**VaR_{t-2} [a] Quintile 2**	**VaR_{t-2} [a] Quintile 3**	**VaR_{t-2} [a] Quintile 4**	**VaR_{t-2} [a] Quintile 5**	**VaR_{t-2} [a] Quintile 1**	**VaR_{t-2} [a] Quintile 2**	**VaR_{t-2} [a] Quintile 3**	**VaR_{t-2} [a] Quintile 4**	**VaR_{t-2} [a] Quintile 5**
N	67	59	61	37	30	34	43	40	65	72
Value-at-Risk Measures										
VAR_{t-1} %	-40.99%	-40.23%	-33.47%	-30.42%	-31.69%	-34.64%	-28.25%	-26.34%	-21.40%	-19.86%
VAR_{t-2} %	-48.60%	-31.86%	-25.12%	-19.28%	-13.55%	-49.02%	-32.17%	-24.61%	-19.25%	-12.25%
VAR_{t-3} %	-29.77%	-29.13%	-29.09%	-22.34%	-22.86%	-33.02%	-28.25%	-23.91%	-21.84%	-19.74%
p-value for test of mean difference $VAR_{t-1}–VAR_{t-3}$	<0.0001	0.0004	0.0534	0.0057	0.0079	0.6129	0.9996	0.3479	0.8144	0.9295
p-value for test of mean difference $VAR_{t-1}–VAR_{t-2}$	0.0021	0.0008	<0.0001	<0.0001	<0.0001	<0.0001	0.0156	.04751	0.1354	<0.0001
Debt ratios										
DAT_{t-1} %	98.68%	88.01%	85.56%	76.07%	71.37%	76.38%	60.17%	59.38%	55.68%	49.81%
DAT_{t-2} %	108.79%	69.44%	74.98%	63.63%	62.48%	86.21%	55.65%	58.04%	53.80%	51.06%
DAT_{t-3} %	69.21%	65.95%	66.73%	61.09%	60.74%	64.54%	51.78%	55.17%	55.89%	52.47%
p-value for test of mean difference $DAT_{t-1}–DAT_{t-3}$	<0.0001	0.0001	<0.0001	0.0002	0.0003	0.1995	0.0276	0.2759	0.8886	0.1024
p-value for test of mean difference $DAT_{t-1}–DAT_{t-2}$	0.7586	0.0008	0.0001	0.0002	<0.0001	0.4551	0.1541	0.5192	0.0702	0.2260

[a] Quintiles are formed by partitioning the full sample by estimates of VaR from two years prior to the bankruptcy filing, where VaR is the lowest monthly market-adjusted return over the previous 12 months (i.e., a nonparametric historical VaR with a confidence level of 91.7 percent).

[b] DAT is the ratio of total debt to book value of assets.

Table 3 Panel B: Mean Value for Estimates of the Probability of Bankruptcy from Logit Models Across Quintiles Determined by VaR_{t-2} and Partitioned by Bankruptcy Status

	Bankrupt Firms					Non-Bankrupt Firms				
Probability of Bankruptcy from Logistic Regression [b]	**VaR_{t-2}** [a] **Quintile 1**	**VaR_{t-2}** [a] **Quintile 2**	**VaR_{t-2}** [a] **Quintile 3**	**VaR_{t-2}** [a] **Quintile 4**	**VaR_{t-2}** [a] **Quintile 5**	**VaR_{t-2}** [a] **Quintile 1**	**VaR_{t-2}** [a] **Quintile 2**	**VaR_{t-2}** [a] **Quintile 3**	**VaR_{t-2}** [a] **Quintile 4**	**VaR_{t-2}** [a] **Quintile 5**
N	67	59	61	37	30	34	43	40	65	72
Models from t−1										
Phat-ALTVaR1 [c]	69.18%	63.05%	57.57%	54.44%	52.62%	53.00%	48.35%	40.72%	34.65%	30.25%
Phat-ALT1 [d]	66.05%	57.38%	55.46%	55.35%	50.45%	48.75%	49.93%	41.86%	39.83%	35.80%
Difference in mean phats	3.13%	5.67%	2.11%	-0.91%	2.17%	4.24%	-1.58%	-1.14%	-5.17%	-5.55%
p-value for test of mean difference phats for t−1	0.0367	0.0002	0.1482	0.6158	0.3789	0.0710	0.2405	0.5350	0.0003	<0.0001
Models from t−2										
Phat-ALTVaR2 [c]	69.35%	55.51%	49.52%	43.24%	38.75%	65.00%	55.30%	45.39%	41.51%	36.02%
Phat-ALT2 [d]	58.17%	52.26%	51.51%	48.58%	47.80%	51.71%	51.97%	46.17%	45.67%	44.97%
Difference in mean phats	11.18%	3.26%	-1.99%	-5.35%	-9.04%	13.28%	3.34%	-0.78%	-4.15%	-8.96%
p-value for test of mean difference phats for t−2	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.0993	<0.0001	<0.0001

[a] Quintiles are formed by partitioning the full sample by estimates of VaR from two years prior to the bankruptcy filing, where VaR is the lowest monthly market-adjusted return over the previous 12 months (i.e., a nonparametric historical VaR with a confidence level of 91.7 percent).

[b] Probability of bankruptcy, Phat, is from the estimates from the logistic regression models.

[c] Phat-ALTVaRn is the probability estimate from the logit model, Phat, n periods prior to the bankruptcy filing expressed as: Probability of $\text{bankruptcy}_{t-n} = f(WCAT_{t-n}, REAT_{t-n}, EBITAT_{t-n}, TAT_{t-n}, MVLT_{t-n}, VaR_{t-n})$, where WCAT is the ratio of working capital to total assets, REAT is the ratio of retained earnings to total assets, EBITAT is the ratio of EBIT to total assets, MVLT is the ratio of market value of equity to book value of total liabilities, and VaR is the lowest monthly market-adjusted return over the previous 12 months.

[d] Phat-ALTn is the probability estimate from the logit model n periods prior to the bankruptcy filing expressed as: Probability of $\text{bankruptcy}_{t-n} = f(WCAT_{t-n}, REAT_{t-n}, EBITAT_{t-n}, TAT_{t-n}, MVLT_{t-n},)$.

Table 4: Cross-Sectional Regressions of Debt-Ratios for Combined Sample of 254 Bankrupt and 254 Non-Bankrupt Firms, Period January 1990 through December 2004 (p-values in parentheses)

$$\frac{Total\ Debt_{t-1}}{Total\ Book\ Value\ of\ Assets} = \alpha_0 + \gamma_1 \Pr(Bankruptcy)_{t-2} + \gamma_2 VaR_{t-2}$$

Variables[a]	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept	0.4303 (<0.0001)	-0.0593 (0.4767)	0.1450 (0.0321)	-0.0667 (0.4143)
$VaR_{i,t-2}$ [a]	-0.0107 (<0.0001)			-0.0065 (<0.0001)
Phat-ALT2 [b]		1.5652 (<0.0001)		1.2234 (<0.0001)
Phat-ALTVaR2 [c]			1.1566 (<0.0001)	
R-square and Adjusted R-square[d]	0.1108	0.1546	0.1350	0.1850

[a] VaR is the lowest monthly market-adjusted return over the previous 12 months, which is a historical VaR with a confidence level of 91.7 percent.

[b] Probability of bankruptcy, Phat, is from the estimates from the logistic regression models, where Phat-ALT2 is the probability estimate from the logit model two years prior to the bankruptcy filing expressed as: Probability of $bankruptcy_{t-2} = f(WCAT_{t-2}, REAT_{t-2}, EBITAT_{t-2}, TAT_{t-2}, MVLT_{t-2}, VaR_{t-2})$, where WCAT is the ratio of working capital to total assets, REAT is the ratio of retained earnings to total assets, EBITAT is the ratio of EBIT to total assets, and MVLT is the ratio of market value of equity to book value of total liabilities.

[c] Probability of bankruptcy, Phat, is from the estimates from the logistic regression models, where Phat-ALTVaR2 is the probability estimate from the logit model two years prior to the bankruptcy filing expressed as: Probability of $bankruptcy_{t-2} = f(WCAT_{t-2}, REAT_{t-2}, EBITAT_{t-2}, TAT_{t-2}, MVLT_{t-2}, VaR_{t-2})$.

[d] The r-square is used for single variable regressions models, and the adjusted R-square is used for multiple regression models.

Table 5: Cross-Sectional Regressions of Debt-Ratios for Bankrupt and Non-Bankrupt Firms Period, January 1990 through December 2004 (p-values in parentheses)

$$\frac{Total\ Debt_{t-1}}{Total\ Book\ Value\ of\ Assets} = \alpha_0 + \gamma_1 \Pr(Bankruptcy)_{t-2} + \gamma_2 VaR_{t-2}$$

	254 Bankrupt Firms				**254 Non-Bankrupt Firms**			
Variables[a]	**Model 1 BR**	**Model 2 BR**	**Model 3 BR**	**Model 4 BR**	**Model 1 NBR**	**Model 2 NBR**	**Model 3 NBR**	**Model 4 NBR**
Intercept	0.5771 (<0.0001)	0.0504 (0.7066)	0.2859 (0.0159)	0.0307 (0.8178)	0.3895 (<0.0001)	0.0939 (0.3273	0.2234 (0.0022)	0.0795 (0.3940)
$VaR_{i,t-2}$	-0.0094 (<0.0001)			-0.0045 (0.0543)	-0.0079 (<0.0001)			-0.0060 (0.0001)
P-hat [b] Model ALT2		1.5501 (<0.0001)		1.3231 (<0.0001)		1.0278 (<0.0001)		0.7528 (0.0003)
P-hat [b] Model ALTVAR2			1.0739 (<0.0001)				0.7773 (<0.0001)	
R-square or Adjusted R-square[d]	0.067	0.1339	0.0927	0.1398	0.1028	0.0970	0.0947	0.1418

[a] VaR is the lowest monthly market-adjusted return over the previous 12 months, which is a historical VaR with a confidence level of 91.7 percent.

[b] Probability of bankruptcy, Phat, is from the estimates from the logistic regression models, where Phat-ALT2 is the probability estimate from the logit model two years prior to the bankruptcy filing expressed as: Probability of bankruptcy$_{t-2}$ = f(WCAT$_{t-2}$, REAT$_{t-2}$, EBITAT$_{t-2}$, TAT$_{t-2}$, MVLT$_{t-2}$,VaR$_{t-2}$), where WCAT is the ratio of working capital to total assets, REAT is the ratio of retained earnings to total assets, EBITAT is the ratio of EBIT to total assets, and MVLT is the ratio of market value of equity to book value of total liabilities.

[c] Probability of Bankruptcy Probability of bankruptcy, Phat, is from the estimates from the logistic regression models, where Phat-ALTVaR2 is the probability estimate from the logit model two years prior to the bankruptcy filing expressed as: Probability of bankruptcy$_{t-2}$ = f(WCAT$_{t-2}$, REAT$_{t-2}$, EBITAT$_{t-2}$, TAT$_{t-2}$, MVLT$_{t-2}$,VaR$_{t-2}$).

[d] The r-square is used for single variable regressions models, and the adjusted R-square is used for multiple regression models.

Appendix: Model Variables and Compustat Descriptions

Traditional Variables

Variable	Description	Compustat Mnemonic
WCAT	Working Capital to Total Assets	WCAP / (AT)
REAT	Retained Earnings to Total Assets	RE / AT
EBITAT	EBIT to Total Assets	OIADP / AT
MVLT	Market Value of Equity / Book Value of Total Liabilities	MKVALF / LT
TAT	Sales to Total Assets	SALE / AT

Other Variables

DAT	Total Debt / Book Value of Assets	DAT
VaRm	Lowest monthly market-adjusted return over the previous 12 months (This historical VaR has a confidence level of 91.7%)	