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Value at Risk and Credit Risk

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Abstract

In recent years increased volatility in interest rates, exchange rates, and other macroeconomic variables has led us to put greater emphasis on risk management. VAR (Value at Risk) has become a common tool to measure an entity's exposure to market risk. But there are few studies to link VAR with credit risk. This study examines the association between the two with three financial statement-based estimates of VARs. Moreover, we investigate whether the term spread and the default spread affect the VAR metrics.

Results indicate that the VAR for speculative grade ratings is significantly higher than that for investment grade ratings. After controlling for the Z-score variables, which have been extensively used amongst credit analysts, we provide strong evidence that the VAR metrics are correlated with the credit ratings. Moreover, the findings suggest that the magnitude of the cash statement VAR is positively related to the term spread and the default spread. However, we could not find evidence that the balance sheet VAR and income statement VAR are affected by the term spread and the default spread.

Key words: Value at Risk, Credit Risk Management, Credit Rating, Default Risk

1. Introduction

In recent decades, a number of quantitative techniques for scoring credits have been developed. One of the classic studies of the credit analysis and bankruptcy were performed by Beaver (1967). Beaver found that a number of accounting ratios from financial statements were associated with high probability of financial distress. More recently, Altman developed the Z-score model to analyze credit risk, based on the values of company financial ratios. The values are weighted and combined to produce a credit risk score. Although these approaches achieve a high accuracy in assessing default risk, the measures used are ad hoc and arbitrarily weighted to score credit risk.

The primary objective of this paper is to provide a comprehensive introduction to the Value- at- risk method (hereafter VAR) of credit analysis. More specifically, we investigate whether the balance sheet VAR, the income statement VAR and cashflow VAR are good indicators of credit risk. Recently we have witnessed tremendous volatility in interest rates, exchange rates, oil prices and stock prices. Also the use of derivative instruments has increased with growth in foreign trade and international finance links among companies. As a result, companies have begun to use the VAR metric for risk management and trading operations. VAR is an amount of losses where the probability of losses exceeding the VAR is at a prespecified level. For example, if a hedge fund assesses that it might lose 50% of its value in one month with a probability of 0.02%, its one month VAR at the 0.02% probability is 50% of its value.

The purpose of our paper is twofold. First, we want to know whether VAR is useful in predicting credit risk. Three different metrics (i.e., the balance sheet VAR, income statement VAR and cashflow statement VAR) have been prepared using the three financial statements. Also we consider each VAR. Secondly, we investigate the association between the new VAR metrics and the underlying risk factors measured as the term spread and default spread (Fama and French; 1989, 1990).

The results show that the VAR for speculative grade ratings is higher than for investment grade rating and statistically significant. Moreover, after controlling for the Z-score variables, which have been extensively used amongst credit analysts, we provide strong evidence that the VAR metrics suggest the credit ratings. Regarding the second research question, the findings suggest that the magnitude of the cash statement VAR is

1) The VAR metric is commonly used to assess the market (price risk) of portfolio of financial assets. Our metric is similar to this but doesn't evaluate a financial portfolio.

correlated with the term spread and the default spread. However, we could not find evidence that the balance sheet VAR and income statement VAR are correlated with the term spread and the default spread.

Our study contributes to the VAR literature and the credit risk measurement literature by introducing a tool for measuring an entity's exposure to credit risk. It will also further our understanding of the links between VAR and credit risk. In addition, these results provide the implications for the credit risk management.

The remainder of this paper is split into 3 sections. Section 2 begins with an account of the sample, then discusses the detailed variable definitions in the empirical procedures. Section 3 lists the results of our empirical tests. Section 4 summarizes the findings and concludes the study.

2. VAR Methodology and Credit Risk Measurement

2.1 What is VAR?

VAR is a summary statistical measure of possible portfolio losses. It presents losses resulting from "normal" market movements. Losses greater than the VAR are suffered only with a specified small probability. The focus of VAR is on the extreme events in the market. Extraordinary events such as the stock market crash of October 1987 and the Asian exchange market crisis of September 1997 are an important issue in risk management. The concept and use of VAR is quite recent. VAR was first introduced by financial firms in the later 1980s to measure the risks of their trading portfolios. Also J.P. Morgan developed its RiskMetrics system, which established a market standard. Now VAR is very widely used by financial institutions, non-financial corporations, and institutional investors. Regulators are also interested in VAR since they are concerned with the protection of the financial system against catastrophic events.

To practice VAR, a parametric method based on extreme value theory is implemented to measure the VAR of a portfolio. The distribution of extreme returns is considered over a long time period. By applying extreme value theory, we can find some useful results about the distribution of extreme returns. One interesting result is that the limiting distribution of extreme returns is largely independent of the distribution of returns itself (See Longin, 2000). The three basic methods of calculating VAR are historical simulation, the delta-normal approach and Monte-Carlo simulation. For our study, the VAR of the financial statement items are measured by the second approach, the delta-normal approach. The delta-normal approach is based on the assumption that the underlying market factors have a multivariate normal distribution. Once the distribution of each selected financial statement item has been obtained, standard mathematical properties of the normal distribution are used to determine the loss that will be equated or exceeded x percent of the time (i.e., the VAR). To illustrate, outcomes less than or equal to 1.65 standard deviations below the mean occur only 5 percent of the time.[2] For the normal distribution, outcomes less than or equal to 1.65 times standard deviation below the mean occur at the 5% level. From the definition of VAR. VAR of each financial item at the 5% probability is:

VAR_i = -[(expected change in each selected financial item) - 1.65*(standard deviation of change in each selected financial item)]

For this analysis, we assume that the expected change in each selected financial item is zero. This assumption is valid for a short time horizon. Since we measure the VARs in each quarter, it is reasonable to have the assumption. The standard deviation, which is a measure of the dispersion of the distribution, is calculated over the estimation period covering all the periods in the sample before the testing period.[3] To compute the incremental VAR, we choose several financial statement items. For example, the cashflow VAR will use items such as cashflows from operating activities, cashflows from investing activities and cashflows from financing activities. Then the VAR values of the financial statement items are summed to the incremental VAR of each company (See Section 3.2).

2) Theory doesn't give any guidance about the choice of x. Conventionally a probability of 1 percent or 5 percent is widely used. We have performed an analysis with a probability of 5%.

3) We eliminate any firms with less than 10 year time series to avoid the outlier effect.

Incremental VAR = Σ VAR_i

To compute the incremental VAR, we assume that the chosen financial items are independent of each other. It follows that the covariance matrix of the selected financial items is ignored. The three VARs measured for the study are the balance sheet VAR, the income statement VAR and the cashflow statement VAR.

2.2 Credit risk measurement

In recent decades, credit risk measurement has innovated dramatically in response to a number of factors, which make its measurement more meaningful. As Altman and Saunders (1998) argue, these factors are: (1) a worldwide structural increase in the number of bankruptcies, (2) a trend towards disintemediation by the highest quality and largest borrowers, (3) more competitive margins on loans, (4) a declining value of real assets in many markets and (5) a dramatic growth of off-balance sheet instruments with inherent default risk exposure.

In multivariate accounting based credit scoring systems, there are two methodological approaches: (1) the discriminant analysis model and (2) the logit model.

Multiple discriminant analysis: Z-score analysis, pioneered by Altman (1968), utilizes discriminant analysis techniques. The model has been refined over time, however the original model took the form:

Z-score = 1.2*[working capital/total assets) + 1.4*[retained earnings/total assets] + 3.3*[EBIT/total assets] + 0.6*[market value of equity/book value of liabilities] + 1.0*[sales/total assets]

The weights are calculated so as to minimize the differences in Z-scores within each group, but to maximize the differences in scores between the two groups. The Z-score indicates the relative likelihood of a firm not going bankrupt.

Logit analysis: Logit analysis is based on different statistical assumptions from discriminant analysis and delivers a score between zero and one that indicates the probability of default. Ohlson (1980) produced a probability of bankruptcy using the values of both ratio-level and categorical univariate measures (See Ohlson, 1980).

But it is unrealistic to expect financial ratios to capture all the information that indicates the probability of default. The weights used to predict the credit risk are arbitrary. In addition, these models are not capable of picking up more subtle and fast-moving changes in borrower conditions as Altman and Saunders (1998) point out. As alternatives to accounting based credit-scoring systems, there have been a number of new approaches.

Other models: Kealhofer (1996) develops a "risk of ruin" model similar to the option pricing models. In his model the value of equity is viewed as a call option on the value of a firm's assets. He attempts to link the observable volatility of a firm's equity value to its unobservable asset value volatility. One problem with their method is whether the volatility of a firm's stock price can be used as an accurate proxy to derive the implied variability in asset values. Recently the application of neural network analysis has been introduced to credit risk classification. Neural network models of credit risk investigate any potential correlations among the explanatory variables in the non-linear bankruptcy prediction function. However, this approach is not built on any clear theoretical foundation. Moreover, Altman, Marco and Varetto (1994) show that the neural network approach did not materially improve the linear discriminant structure.

In summary, although credit risk measurement has been developed over the last 20 years, most of the models don't have any satisfactory underpinning in theory and are results of "fishing expeditions" of the data. This leads us to seek a better credit risk measurement.

The probability of default is the sum of the probabilities of scenarios in which default occurs. Following Penman's notation (Penman, 2000), the default probability is

Probability of Default = Pr[Cash Available for Debt Service < Debt Service Requirement]

where Pr is probability.

And the formal definition of VAR is given by

Prespecified Probability = Pr [$\Delta P_t \leqq$ VAR]

where ΔP_t is the change in market value of a financial asset over a period t.

From the equation above, we predict that firms are more likely to be financially distressed as the magnitude of VAR increases. In the next section, detailed descriptions of our methodology are advanced for tests of our prediction.

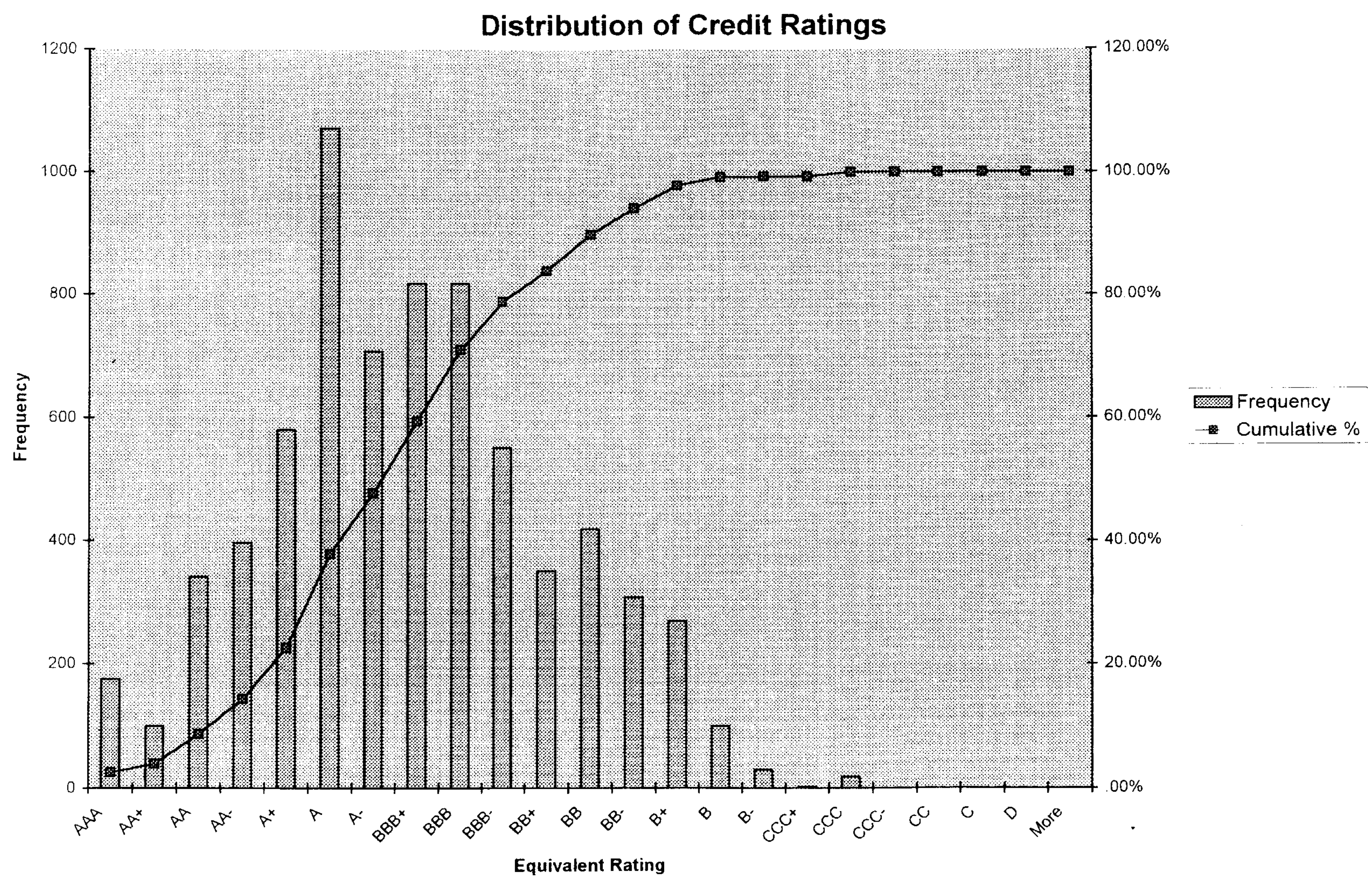

Figure 1. Illustrates the distribution of Credit Rating for the Total Sample (1994-1998).

3. Research Design

3.1 Data

Rating agencies specialize in evaluating the credit risk of firms. The four major U.S. rating agencies are Moody's Investors Service, Standard & Poor's (S&P), Fitch IBCA and Duff and Phelps Credit Rating Co. We use data gathered from Standard & Poor's. The data covers the credit ratings for 510 firms between 1994 and 1998. Table 1 presents the number of credit ratings for each year. 1,803 firm quarters from regulated industries are eliminated. The S&P data are combined with quarterly accounting data from Compustat. Out of 9,197 firm quarters, additional 752 firm quarters are deleted since observations on the S&P data are not available on Compustat. We further require firms to have at least 40 quarters before the testing period.[4] The filtering rules provide 7,062 firm quarters and 348 firms. For the tests, we quantify bond ratings as shown in Table 2. A firm with a high score is more likely to be exposed to credit risk.

3.2 Independent Variables and Control Variables

Our tests investigate whether the balance sheet VAR, the

Table 1. Sample Criteria

S&P Bond rating (1994-1998)	11,000
Delete regulated industries*	1,803
Delete firm quarters not available on Compustat	752
Delete firms having less than 40 firm quarters before 1994	1,383
Final Sample	7,062

* Sample All firms in the SIC 48xx (Communications), 49xx (Electric, Gas and Sanitary Service) and 61xx-69xx (Financial industries) are deleted.

4) To compute a standard deviation, we chose only firms with more than or equal to 40 quarters during the estimation period.

Table 2. Transformation of Bond Ratings from Standard and Poor's

AAA	1.0	AA+	1.75	A+	2.75
		AA	2.0	A	3.0
		AA-	2.25	A-	3.25
BBB+	3.75	BB+	4.75	B+	5.75
BBB	4.0	BB	5.0	B	6.0
BBB-	4.25	BB-	5.25	B-	6.25
CCC+	6.75	CC+	7.75	C+	8.75
CCC	7.0	CC	8.0	C	9.0
CCC-	7.25	CC-	8.25	C-	9.25

income statement VAR and cashflow VAR are good indicators of credit risk.

To summarize notation and definitions of the components of the independent variables:

VaR(B/S)=VaR(Assets)+VaR(Debt)
where
VaR(Assets)=VaR(Current Assets)+VaR(Property Plant & Equipment)
VaR(Debt)=VaR(Current Liabilities)+VaR(Long-term Debt)
VaR(I/S)=VaR(Operating Income)+VaR(Non-operating Income) +VaR(Special Items)+VaR(Interest Expense)
VaR(Cash-flow)=VaR(Operating Cashflow)+VaR(Investing Cashflow)+VaR(Financing Cashflow)

However, the effect of these VARs on credit risk may be subsumed by the accounting based financial ratios. So we include Altman's (1968) financial ratios for control variables as presented in section 2. Additionally, we control for the firm size and industry effects.

4. Empirical Results

4.1 Descriptive Statistics

Table 3 provides descriptive statistics on control variables between the investment grade rating and speculative grade

Table 3. Descriptive Statistics on Control Variables by S&P Bond Rating

Mean (Median)

US rating	Investment Grade Rating (N=5,564)	Speculative Grade Rating (N=1,498)	t-test of difference	z-stat for ranksum test
X1	0.1275(0.1134)	0.1605(0.1505)	-7.6325**	-7.5948**
X2	0.3121(0.3009)	-0.048 (0.0372)	48.9045**	41.5575**
X3	0.0238(0.0231)	0.0053(0.0091)	19.9233**	25.9783**
X4	1.2909(0.9815)	0.6310(0.4496)	22.9630**	32.2546**
X5	0.3080(0.2694)	0.2905(0.2681)	3.1809**	2.4858**
Zscore	0.3332(0.2912)	0.3028(0.2760)	4.8625**	5.7092**
Firm Size	11368.39(4019.22)	1354.68(604.52)	16.7930**	43.4108**
Idum	0.1917(0.0000)	0.1415(0.0000)	4.4881**	4.4820**

Investment grade rating provided that rating is better than or equal to BBB-, speculative grade rating otherwise.
X1 = working capital /total assets.
X2 = retained earnings/total assets.
X3 = EBIT/total assets.
X4 = market value of equity/book value of liabilities.
X5 = sales/total assets.
Z = 0.012(X1) + 0.014(X2) + 0.033(X3) + 0.006*X4 + 0.999(X5).
Firm Size is # of shares outstanding * closing price per share in the third month of the quarter.
Idum is 1 if the firm is in a high-tech industry, otherwise 0.
Firms with the following SIC codes are considered as high-tech firms.

2833 - 2836 (Chemicals & Allied Products)
3570 - 3577 (Indl, Comml Machinery and Computer Eq.)
3600 - 3674 (Electr, Other Electr Eq and Ex Comp)
5200 - 5961 (Bldg Matl, Hardwr and Garden Rental)
7370 - 7374 (Business Service)

* significant at the 5% level.
** significant at the 1% level.

rating. For the investment grade rating, we include firm quarters with better than or equal to BBB- while other firm quarters with less than BBB- are classified as speculative grade, consistent with the classification by Standard & Poor's. The results indicate that the five financial ratios are significant at p-values less than

0.01. Consistent with Altman's (1968) results, the investment grade rating has a higher Z-score than the speculative rating. Interestingly, firm size and industry dummy are significantly different between the two groups. The larger a firm is, the less likely it is to be exposed to credit risk. Moreover, firms in certain industries may have a better credit rating. For example, high tech companies tend to have a better credit rating.

4.2 Comparison of VARs between investment grade and speculative grade

Figure 2 and Table 4 provide the difference of VARs between investment grade and speculative grade. Consistent with our prediction, the speculative grade group has higher VARs at p-values less than 0.01. Additionally, a breakdown of VARs by years is reported in Table 5. It shows that the results of Table 4 holds in each year. Collectively, these indicate that for the speculative group, the VARs are higher than for the investment grade group.

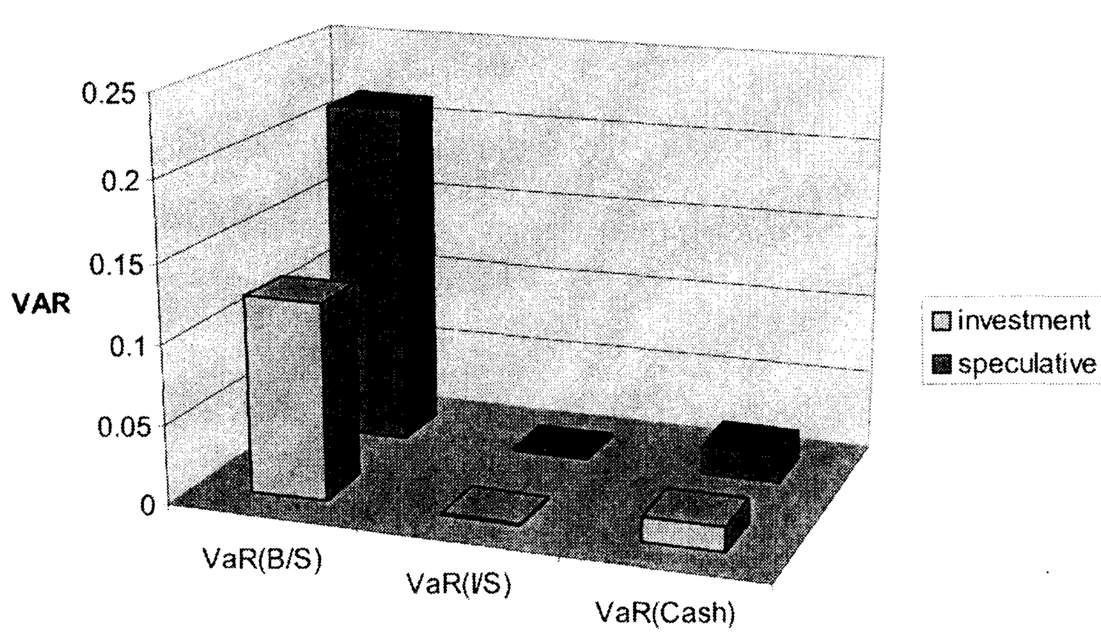

Figure 2. compares the mean of VARs between investment grade and speculative grade.
Bonds are classified as investment grade provided that the rating is better than or equal to BBB-, speculative grade rating otherwise.
See Table 5 for the definition of the VARs.

Table 4. Descriptive Statistics on VaR by S&P Bond Rating

Mean (Median)

US rating	Investment Grade Rating (N=5,564)	Speculative Grade Rating (N=1,498)	t-test of difference	z-stat for ranksum test
VaR (B/S)	0.1239(0.1104)	0.2154(0.1723)	-34.8809**	-31.8907**
VaR (I/S)	0.0013(0.0009)	0.0016(0.0010)	-4.8756**	-5.9425**
VaR (Cashflows)	0.0158(0.0105)	0.0177(0.0106)	-3.4429**	-1.4540**

Investment grade rating provided that rating is better than or equal to BBB-, speculative grade rating otherwise.
VaR(B/S) = VaR(Assets) + VaR(Debt).
VaR(I/S) = VaR(Operating Income) + VaR(Non-operating Income) + VaR(Special Items) + VaR(Interest Expense).
VaR(Cashflows) = VaR(Operating Cashflows) + VaR(Investing Cashflows) + VaR(Financing Cashflows).

* significant at the 5% level.
** significant at the 1% level.

4.3 Determinants of credit risk

Our main research question is whether the VARs developed here have incremental explanatory power over Altman's Z-score for credit rating level. As postulated in section 2.2, we assert that firms are more likely to get a lower credit rating as the magnitude of VAR increases. Since Altman's Z-score is widely used to measure credit risk, we include the five variables to examine any incremental effect of VAR after controlling for the ratios. Additionally, firm size may indicate risk (Banz, 1981). Small firms tend to have lower bond ratings (Kaplan and Urwitz, 1979). Thus firm size is included as a control variable. Also firms in a high-tech industry may have a different risk structure relative to other firms. Consistent with Kaznick and Lev's (1995) classification, we use an industry indicator variable to control the industry effect as well. To test the association between credit risk and VARs, we estimate the following regressions:

Table 5. Determinants of Credit Risk

Variable	Regression 1	Regression 2	Regression3	Regression4
Intercept	4.1597**	4.3963**	4.3451**	4.1267**
VaR (B/S)	1.5906**			1.4505**
VaR (I/S)		20.8630**		9.3050
VaR (Cashflow)			4.3393**	3.1965**
X1	1.2215**	1.1888**	1.2406**	1.2129**
X2	-1.8906**	-2.2026**	-2.1955**	-1.8781**
X3	-1.1925**	-0.8897*	-0.9014*	-1.0632**
X4	-0.1939**	-0.1775**	-0.1868**	-0.2207**
X5	-0.3844**	-0.3073**	-0.2791**	-0.3515**
Firm Size	-0.0000096**	-0.0000104**	-0.0000101**	-0.0000090**
Idum	0.0252	-0.0344	-0.0264	-0.0365
Adj R-Sq	0.5633	0.5532	0.5565	0.5659

Dependent Variable is credit rating scores consistent with Cho and Yu(1998)'s.
VaR(B/S) = VaR(Assets) + VaR(Debt).
VaR(I/S) = VaR(Operating Income) + VaR(Non-operating Income) + VaR(Special Items) + VaR(Interest Expense).
VaR(Cashflows) = VaR(Operating Cashflows) + VaR(Investing Cashflows) + VaR(Financing Cashflows).
The ratios X1 through X5 are the variables in the Altman's Z-score model.
X1 is Working capital/Total assets.
X2 is Retained earnings/Total assets.
X3 is EBIT/Total assets.
X4 is Market value of equity/Book value of liabilities.
X5 is Sales/Total assets.
Zscore = 0.012(X1) + 0.014(X2) + 0.033(X3) + 0.006(X4) + 0.999(X5)
Firm Size is # of shares outstanding * closing price per share in the third month of the quarter.
Idum is 1 if the firm is in a high-tech industry, otherwise 0.
Firms with the following SIC codes are considered as high-tech firms.

2833 - 2836 (Chemicals & Allied Products)
3570 - 3577 (Indl, Comml Machinery and Computer Eq.)
3600 - 3674 (Electr, Other Electr Eq and Ex Comp)
5200 - 5961 (Bldg Matl, Hardwr and Garden Rental)
7370 - 7374 (Business Service)

* significant at the 5% level.
** significant at the 1 % level.

$$\begin{aligned}\text{CreditRating}_{it} = {} & \beta_0 + \beta_1 VaR(B/S)_{it} + \beta_2 X1_{it} + \beta_3 X2_{it} \\ & + \beta_4 X3_{it} + \beta_5 X4_{it} + \beta_6 X5_{it} + \beta_7 \text{Size}_{it} \\ & + \beta_8 \text{Idum}_{it} \end{aligned} \tag{1}$$

$$\begin{aligned}\text{CreditRating}_{it} = {} & \beta_0 + \beta_1 VaR(I/S)_{it} + \beta_2 X1_{it} + \beta_3 X2_{it} \\ & + \beta_4 X3_{it} + \beta_5 X4_{it} + \beta_6 X5_{it} + \beta_7 \text{Size}_{it} \\ & + \beta_8 \text{Idum}_{it} \end{aligned} \tag{2}$$

$$\begin{aligned}\text{CreditRating}_{it} = {} & \beta_0 + \beta_1 VaR(\text{Cashflow})_{it} + \beta_2 X1_{it} + \beta_3 X2_{it} \\ & + \beta_4 X3_{it} + \beta_5 X4_{it} + \beta_6 X5_{it} + \beta_7 \text{Size}_{it} \\ & + \beta_8 \text{Idum}_{it} \end{aligned} \tag{3}$$

$$\begin{aligned}\text{CreditRating}_{it} = {} & \beta_0 + \beta_1 VaR(\text{B}/\text{S})_{it} + \beta_2 VaR(\text{I}/\text{S})_{it} \\ & + \beta_3 VaR(\text{Cashflow})_{it} + \beta_4 X1_{it} \\ & + \beta_5 X2_{it} + \beta_6 X3_{it} + \beta_7 X4_{it} + \beta_8 X5_{it} \\ & + \beta_9 \text{Size}_{it} + \beta_{10} \text{Idum}_{it} \end{aligned} \tag{4}$$

where $VaR(B/S)=VaR(\text{Assets})+VaR(\text{Debt})$.

$VaR(I/S)=VaR(\text{Operating Income})+VaR(\text{Non-operating Income})+VaR(\text{Special Items})+VaR(\text{Interest Expense})$.

$VaR(\text{Cashflows})=VaR(\text{Operating Cashflows})+VaR(\text{Investing Cashflows})+VaR(\text{Financing Cashflows})$.

The ratios $X1$ through $X5$ are the variables in the Altman's Z-score model.

$X1$ is Working capital/Total assets.

$X2$ is Retained earnings/Total assets.

$X3$ is EBIT/Total assets.

$X4$ is Market value of equity/Book value of liabilities.

$X5$ is Sales/Total assets.

Firm Size is # of shares outstanding * closing price per share in the third month of the quarter.

Idum is 1 if the firm is in a high-tech industry, otherwise 0.

A significantly positive coefficient on β_1 for the regression (1), (2) and (3) is consistent with VARs increasing credit risk. For the regression equation (4), we predict that the sign of β_1, β_2 and β_3

Table 6. Correlation Matrix

Variables	Rating	X1	X2	X3	X4	X5	Size	Idum	VaR (B/S)	VaR (I/S)	VaR (Cashflow)
Rating	1.00	0.09	-0.63	-0.32	-0.47	-0.02	-0.44	-0.15	0.42	0.05	0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
X1		1.00	0.12	0.09	0.05	0.18	-0.09	0.17	-0.02	0.14	-0.008
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.00)	(0.49)
X2			1.00	0.39	0.40	0.06	0.23	0.08	-0.58	-0.06	-0.04
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
X3				1.00	0.41	0.12	0.19	0.10	-0.12	-0.00	0.01
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.50)	(0.36)
X4					1.00	0.03	0.50	0.24	-0.09	0.28	0.16
					(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
X5						1.00	-0.08	0.12	0.06	0.03	-0.08
						(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Size							1.00	0.28	0.15	0.00	-0.00
							(0.00)	(0.00)	(0.00)	(0.67)	(0.64)
Idum								1.00	-0.00	0.16	0.02
								(0.00)	(0.43)	(0.00)	(0.03)
VaR									1.00	0.19	0.17
(B/S)									(0.00)	(0.00)	(0.00)
VaR										1.00	0.25
(I/S)										(0.00)	(0.00)
VaR											1.00
(Cashflow)											(0.00)

See table 5 for definition of variables.
Pearson correlations shown.
P-values in the parentheses.

is positive. As predicted, the coefficient on the VARs in Table 6 is significantly positive at less than the 1% level except the β_2 for $VaR(I/S)$ from the regression (4).[5] The results of these regressions provide evidence that the three VARs are positively associated with credit risk.

5) Although the coefficient on *VaR*(I/S) in (2) is significantly positive, the regression results in (4) indicate that the β_2 in (4) is insignificant. Table 6 shows that the correlations between *VaR*(B/S), *VaR*(I/S) and *VaR*(Cashflow) are significantly positive. So it appears that the multicollinearity problem subsumes the effect of *VaR*(I/S) in the regression (4).

4.4 Macroeconomy and VAR

To add the understanding of the association between VAR and credit risk, we further identify some underlying factors, which affect the magnitude of VAR. Jonkhart (1979) and Iben and Litterman (1989) derive implied probabilities of default from the term structure of yield spread between default free and risky corporate securities. Also Fama and French (1989, 1990) and Chen (1991) postulate that the term structure and the default spread reflect economic conditions. Consequently, we are motivated to examine whether the two variables are associated with the magnitude of VAR.

Specifically, under general assumptions, the term structure of interest rates is related to the expected growth rates of GNP and consumption. The intuition is that if future output is expected to be high, individuals desire to smooth consumption by attempting to borrow against the expected future production, thereby bidding up interest rates. Additionally, it is believed that the default spread reflects the health of the economy (Chen, Roll, and Ross, 1986; Fama and French, 1989 & 1990; Chen, 1991). Consistent with Fama and French's measures, the term structure and the default risk are obtained from Ibbotson & Associate Yearbook (2000).

To test whether VAR is affected by the two variables we run the following regressions:

$$VaR(B/S)_{it} = \beta_0 + \beta_1 \mathrm{Term}_{it} + \beta_2 \mathrm{Default}_{it} \tag{4}$$

$$VaR(I/S)_{it} = \beta_0 + \beta_1 \mathrm{Term}_{it} + \beta_2 \mathrm{Default}_{it} \tag{5}$$

$$VaR(\mathrm{Cashflow})_{it} = \beta_0 + \beta_1 \mathrm{Term}_{it} + \beta_2 \mathrm{Default}_{it} \tag{6}$$

where Default is referred to as the default spread which is defined as the net return from investing in long-term corporate bonds rather than long-term government bonds of equal maturity.

Term is the term spread, which is derived as the geometric difference between total returns on long-term government bonds and U.S. 30-day Treasury Bills.

Table 7. Comparison of *VaR*(*B/S*), *VaR*(*I/S*) and *VaR*(Cashflows) between investment grade and speculative grade (1994-1998)

Mean (Median)

Rating	1994 B/S	1994 I/S	1994 Cashflows	1995 B/S	1995 I/S	1995 Cashflows	1996 B/S	1996 I/S	1996 Cashflows
Investment Grade Rating									
	0.123	0.001	0.015	0.123	0.001	0.015	0.122	0.001	0.016
	(0.108)	(0.0008)	(0.009)	(0.109)	(0.0009)	(0.010)	(0.110)	(0.0009)	(0.010)
Speculative Grade Rating									
	0.231	0.0017	0.017	0.225	0.0015	0.014	0.212	0.0017	0.018
	(0.185)	(0.0009)	(0.010)	(0.171)	(0.001)	(0.010)	(0.167)	(0.001)	(0.011)

	1997 B/S	1997 I/S	1997 Cashflows	1998 B/S	1998 I/S	1998 Cashflows
Investment Grade Rating						
	0.125	0.0014	0.016	0.125	0.0013	0.0164
	(0.111)	(0.0009)	(0.011)	(0.112)	(0.0009)	(0.010)
Speculative Grade Rating						
	0.205	0.0016	0.0167	0.201	0.0016	0.021
	(0.162)	(0.001)	(0.010)	(0.175)	(0.001)	(0.012)

Investment grade rating provided that rating is better than or equal to BBB-, speculative grade rating otherwise.

VaR(*B/S*)=*VaR*(Assets)+*VaR*(Debt).

VaR(*I/S*)=*VaR*(Operating Income)+*VaR*(Non-operating Income)+*VaR*(Special Items)+*VaR*(Interest Expense).

VaR(Cashflows)=*VaR*(Operating Cashflows)+*VaR*(Investing Cashflows)+ *VaR*(Financing Cashflows).

The findings in Table 7 report that *VaR*(*B/S*) and *VaR*(*I/S*) are not related to the term structure and the default spread. However, the last column of Table 7 shows that *VaR*(Cashflow) is positively affected by the two variables and statistically significant. Other than the above variables, the risk induced by exchange rates may play a role. As Altman (1995) and Cho and Yu (1999) argue, volatility in exchange rates comes into play in a credit crunch in an emerging market economy. However, in the US the effect of volatility in exchange rates on VARs seems insignificant.[6]

Table 8. VaR and the Macroeconomy

Variable	*VaR*(*B/S*)	*VaR*(*I/S*)	*VaR*(Cashflows)
Intercept	0.1456**	0.0014**	0.0161**
Default	-0.1016	0.0053	0.3720**
Term	-0.0406	0.0021	0.1439**
Adj R-Sq	-0.0003	-0.0001	0.0165

Dependent Variable are *VaR*(*B/S*), *VaR*(*I/S*) and *VaR*(Cashflows) respectively.
VaR(*B/S*)=*VaR*(Assets)+*VaR*(Debt).
VaR(*I/S*)=*VaR*(Operating Income)+*VaR*(Non-operating Income)+ *VaR*(Special Items)+*VaR*(Interest Expense).
VaR(Cashflows)=*VaR*(Operating Cashflows)+*VaR*(Investing Cashflows)+ *VaR*(Financing Cashflows).
Default is referred to as the default spread which defined as the net return from investing in long-term corporate bonds rather than long-term government bonds of equal maturity.
Term is the term spread which is derived as the geometric difference between total returns on long-term government bonds and U.S. 30 day treasury bills.

5. Conclusion

This paper examines the association between VAR and credit risk. This paper is the first step in examining whether VAR can be used to assess credit risk. The results show that the VAR for speculative grade ratings is higher than for investment grade ratings and statistically significant. After controlling for the Z-score variables, which have been extensively used amongst credit analysts, we provide strong evidence that the VAR metrics are closely related to credit ratings. Also we find that the cash statement VAR is positively related to the term spread and the default spread. However, we could not find evidence that the balance sheet VAR and income statement VAR are correlated with the term spread and the default spread.

6) According to our sensitivity tests, the foreign currency adjustment item (item 34 in Quarterly Compustat) appears to be trivial in most of the sample firms.

Our study provides some implications. First, from the corporate perspective, the VARs discussed here may be used to manage credit risk. Second, for credit analysts, the VAR based on financial statements can improve the quality of credit risk measurement procedure. Furthermore, the results provide the regulation authorities with some policy implications. For example, the three VAR metrics may be used as standards for quantitative disclosures of risk in quarterly or annual reports.[7]

Finally, additional work needs to be done for a more refined measure of VAR by breaking down the financial items. For further study, it is interesting to explore what additional financial statement items are associated with VAR.

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7) FAS No.119 is an example of disclosure of market risk. However, the disclosure requirements in FAS No. 119 are limited to derivative financial instruments. In addition it encourages but does not require disclosure of quantitative information about an entity's net market risk exposures.

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