Empirical Study of Credit Risk Measurement in Manufacturing Industry: Based on Financial and Market Information[3]

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Abstract: This paper aims to analyze the accuracy and effectiveness to predict the credit risk and the internal relationships between the KMV model based on market information and the Logistic model based on financial information, so that empirical basis can be provided for measuring the credit risk in manufacturing industry. This paper shows that it is feasible and advantageous to combine KMV Model with Logistic Model to measure the credit risk in manufacturing industry, by using the data of Chinese listed manufacturing companies between 2001 and 2009 as the reseach sample.
Keywords: KMV model; Logistic model; Credit risk; Manufacturing industry

1 Introduction

Resulting from rapid development in recent years, manufacturing industry has become an important part of listed companies. However, due to funding problems,many manufacturing enterprises get into trouble or even go bankruptcy.[4] Manufacturing industry are dominated by SMEs, which may result in credit risk and restrict their development. Therefore, study on manufacturing industry from the perspective of bank is of great practical significance.

Quantitative study on credit risk has two main ideas. One is based on financial information,such as z-score model, ZETA model, Logistic regression model and so on. Another is based on marketing information, which refers to western mainstream commercial credit risk measurement models, for example, Credit Risk plus model, KMV model, Credit Metrics model and Credit Portfolio View, etc.

Sobehart, Keenan and Stein(2000) [1]compared six credit risk models by forward test technology, and found that KMV model has highest precision of risk prediction and relatively lower misjudgement ratio. Similar conclusion can be seen in Kedlhofer and Kurbat(2001) [2], Korablev and Dwyer(2007) [6]. Kang et al. (2009) [7] modified KMV model by changing the way of pricing non-current stock and setting default point, their empirical study showed that the modification improved the sensitivity of KMV model forecasting and distinguishing.Anthony (2001)[3] concluded that the prediction accuracy of log-logistic model is higher than Probit model. Tan (2005) [4] added DD to Logistic model, and found that, to some extent, DD can improve the explanation and prediction ability of model.Later Shi(2007) [5] made an empirical study on boundary logistic default model and praised its predictive efficiency.

All in all, due to the delay,distorition and other characteristics of financial information, the predicition ability of Logistic model is constrained. So in this article, we firstly modify KMV model by dynamic modification of default point and default timing. Secondly, we analyse the recognition capability of credit risk, and compare the relative factors impact effect and risk predictive ability by default distance and expected default frequency which are output of KMV model. And then, we introduce DD to Logistic model and construct a DD-Logistic model based on an overall consideration of financial and marketing information. Finally, we make the empirical study on manufacturing industry.

2 Research Design

2.1KMV model and its modification

2.1.1KMV model principal and calculation procedure

(1) Calculating market value and volatility of asset

KMV model assume that default occurs when asset value is less than the liability of company. That is to say, KMV model view equity as call option of company asset, and debt of company is the exercise price. Then the value of European call option can be calculated according to BSM model.

$$V_E = V_A N(d_1) - e^{-rT} DN(d_2) \tag{1}$$

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[4] There are sixty four enterprises get special treated in Shanghai and Shenzhen market in 2009,which is 7.4% of total number of listed manufacturing companies,and account for 51.2% of special treated companies in the same year.

where $$d_1 = \frac{\ln(V_A / D) + (r + \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{\tau}} \tag{2}$$

$$d_2 = d_1 - \sigma_A \sqrt{T} \tag{3}$$

V_E is market value of equity, and face value of debt is noted D. V_A represents market value of asset. r is risk-free rate, and T is corporate debt maturity. σ_A decotes volatility of asset and $N(.)$ is cumulative distribution function of standard normal distribution.

In addition, KMV model reveals the theoretical relationship between volatility of equity and asset.

$$\sigma_E = \frac{N(d_1)V_A\sigma_A}{V_E} \tag{4}$$

Where σ_E denotes volatility of equity.

Asset value and volatility can be determined by solving the equations (1)-(4) simultaneously.

(2) Calculating DD(distance to default)

KMV first determines default point, the empirical formula is $DP = SD + LD/2$, where SD is current debt and LD is long-term debt. Then DD can be calculated.Assuming market value of asset submits to lognormal distribution,

$$DD = \frac{E(V_A) - DP}{E(V_A)\sigma_A} = \frac{\ln(\frac{V_A}{D}) + (\mu - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}} \tag{5}$$

DD is the multiple of distance between future expected value of asset after T years and default point compared to the standard deviation of asset,which indicates credit status of companies.In general,the larger the DD value is, meaning expected asset value is farther from default point,the less likely the default occurs and the better the credit status is.Conversely,the worse the credit situation is. [9]

(3) Calculating EDF(expected default frequency)

Under log-normal assumption,the EDF of company is

$$P_T = N(-d_2) = N(-DD) \tag{6}$$

2.1.2 Modify the KMV model

Standard KMV model assume that default point is constant and default only occurs on due date. However,debt contracts often contain some security provisions, for instance, creditor can be allowed to reorganize the company when asset value is less than a certain threshold. This means that default point don't always equal to debt and default timing is not only on expiry date. As a matter of fact, it is stochastic. In this paper we borrow ideas from Kang(2009) [7] and modify KMV model by dynamic default point and stochastic default timing.

(1) Stochastic modification of default timing

Assume that default point equals to the fixed empirical value between zero and the starting value of asset. Default timing is an random continuous variable, $\tau = \inf\{t > 0 : V^t < D(t)\}$, and default probability is

$$P_T = N(\frac{\ln(\frac{D}{V}) - mT}{\sigma_A \cdot \sqrt{T}}) + (\frac{DP_T}{V_A})^{\frac{2m}{\sigma_A^2}} N(\frac{\ln(\frac{DP_T^2}{D \cdot V_A}) + mT}{\sigma_A \cdot \sqrt{T}}) \tag{7}$$

Where $m = \mu - \frac{\sigma_A^2}{2}$, and is replaced by risk-free rate.

Corresponding distance to default is

$$DD = \frac{\ln(\frac{V_A}{SD + LD/2}) + (\mu - \frac{\sigma_A^2}{2})T}{\sigma_A \cdot \sqrt{T}} \tag{8}$$

(2) Dynamic modification of default point

Assume that default point is a dynamic random variable, $D(t) = De^{-k(T-t)}$, which means face value of debt on t by discounting at continuous discount rate k. And default probability is

$$P_T = N\left(\frac{\ln(\frac{D}{V_A}) - mT}{\sigma_A \cdot \sqrt{T}}\right) + \left(\frac{De^{kT}}{V_A}\right)^{\frac{2(m-k)}{\sigma_A^2}} N\left(\frac{\ln(\frac{D}{V_A}) + (m-2k)T}{\sigma_A \cdot \sqrt{T}}\right)^{[6]} \tag{9}$$

Corresponding distance to default is

$$DD = \frac{\ln(\frac{V_A}{De^{-k(T-t)}}) + (\mu - \frac{1}{2}\sigma_A^2)T}{\sigma_A \cdot \sqrt{T}} \tag{10}$$

2.2 Parameters setup in KMV model

2.2.1 Volatility of market value of equity

As we know, Chinese stock market is not in full circulation. So in this paper we use closing daily data of A-share enterprises in manufacturing industry is used to represent the equity volatility. Tests show ARCH effect doesn't exist in many stock return series. In addition, Shi et al.(2005) concludes that GARCH model may underestimate stock price volatility and it fits China stock market not well. Therefore, we calculate equity volatility by historic estimation.

Daily stock return is

$$u_i = \ln(S_i / S_{i-1}) \tag{11}$$

Where S_i is i-th closing price of stock.

Daily volatility of stock is

$$\sigma'_E = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(u_i - \bar{u})^2} \tag{12}$$

Where $\bar{u}$ is mean of daily stock returns,and n is the number of trading days in one year. So yearly volatility of stock price is

$$\sigma_E = \sigma'_E \times \sqrt{250} \tag{13}$$

2.2.2 Market value of equity

According to Zhang (2007), we calculate market value of non-current stock by regression.

Market Value of Equity=Curent market value+Non-current market value

=Daily closing price*Outstanding shares+(0.99576+0.60973*Asset per share)*State-own shares (14)

Where state-own shares represent illiquid shares approximately.

2.2.3 Face value of debt, debt maturity, discount rate and risk-free rate

Face value of debt is assumed to be nominal value of total liabilities in financial report.Debt maturity is one year, and the discount rate is risk-free rate.Deposit interest of lump year on a regular basis is used as risk-free rate.If there is several adjustments in annual interest rate.It can be replaced by geometric mean to decrease the effects of extreme value.

Table 1 Deposit Interest of Lump Year on a Regular Basis

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009
Annual Interest Rate (%)	2.25	1.98	1.98	2.25	2.25	2.52	3.46	3.06	2.25

2.2.4 Data specification

Samples consist of eighty-four listed companies in manufacturing industry, including twenty- six *Special Treated* companies and fifty-eight *non Special Treated* companies. Considering the difference of A-shares, B-shares and H-shares, we choose samples which went public in Shanghai and Shenzhen stock exchange before 1998 and only issued A-shares. Furthermore, full financial statements and transaction data of them can be obtained. Then we replace obvious error and unreasonable data by linear fitting method in SPSS. All data is from series research database of CSMAR GuoTaiAn.

2.3 Logistic model

Residuals of Logistic model obey two values discrete distribution, and maximum likelyhood estimation can be used to estimate the model parameters. Logistic model fits for cases where explained variables are two values, 0 and 1. Moreover, unlike other regression model, it requires no normal distribution assumption and can be used to calculate default probability of companies.

$$Logitp_i = \ln(\frac{p_i}{1-p_i}) = \beta_0 + \sum_{k=1}^{m} \beta_k x_{ki} \tag{15}$$

$$p_i = \frac{1}{1+\exp[-(\beta_0 + \sum_{k=1}^{m} \beta_k x_{ki})]} \tag{16}$$

Where x_{ki} denotes i-th explanatory variable of i-th sample, β_k is technical coefficient, obtained by maximum likelyhood estimation. p_i represents default probability of i-th sample and i ranges from one to n.

3 Empirical Study on KMV Model

3.1 Analysis of credit risk recognition capability of KMV model

3.1.1 Trend analysis of distance to default and expected default frequency

First, Figure 1 shows that values of DD and EDF shift. Mean of DD decreases in years from 2003 to 2008, yet mean of EDF increases,which indicates the increasing default risk in manufacturing industry. Second, mean curve of DD of *Group ST(Special Treated)* is lower than that of *Non ST Group*, otherwise, its mean curve of EDF is higher than that of *Non ST Group*, which means the higher default risk of *ST Group*. Third, mean difference curve suggests that mean difference of DD had been decreasing year by year, even a positive value appeared in 2008. Meanwhile, there was large negative mean difference of EDF, which was narrowed in 2009. Evidence from economics shows that immence demand elasticity of manufacturing industry results in weak ability of withstanding market risk. The government adopted relatively tight credit policy to overcome the international inflation in 2007. Meanwhile, affected by American subprime crisis, external demand of Chinese manufacturing industry nosedived, and sales and productions were hindered, which brought about larger credit risk. For the sake of their own security, banks strengthened credit supervision of corporations especially of thise with bad credit status. DD of *ST Group* is but greater than that of *Non ST Group*, which illustrated that default risk had been effectively controlled.

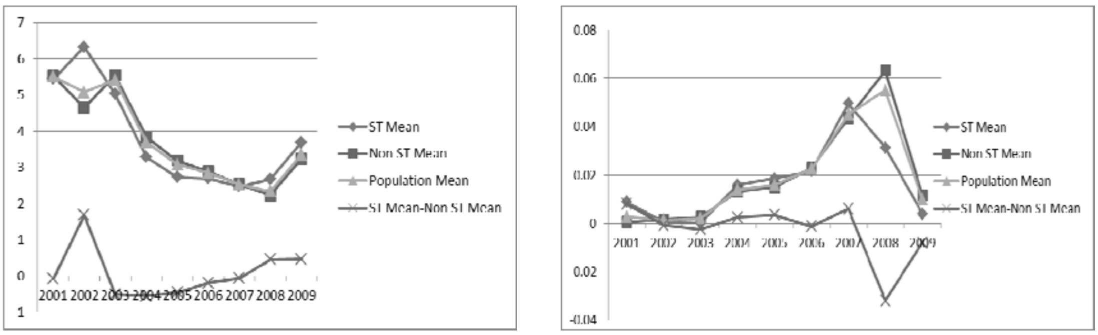

Figure 1 Trend of Distance to Default(Left) and Expected Default Frequency(Right) From 2001 to 2009

3.1.2 Correlation analysis of DD and EDF

It can be seen from Figure 2, there is negative correlation between DD and EDF. DD of samples gathers in interval [2, 3], which means, in accordance with current situation of manufacturing industry, most of manufacturers tends to default. It is worth noting that EDF is not a good indicator of default risk. Because it generally maintains zero and fails to predict default risk after DD is more than five.

3.1.3 Significance analysis of DD

Examining distinguishing capability between *ST* Group and *Non ST Group* by non parameter testing method of two independent sample, associated probability of DD were respectively 0.049 and 0.034, less than significant level 0.05 whether in K-S test or U test.That is to say, DD of *ST Group* and *Non ST Group* is significantly unequal under 95% confidence level and DD is able to distinguish between *ST Group* and *Non ST Group* significantly.

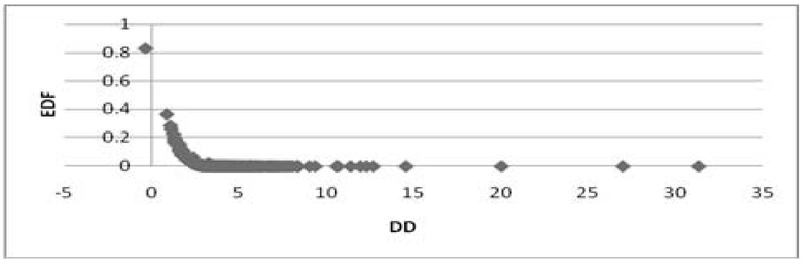

Figure 2 Relation of DD and EDF

3.2 Effect of relative factors on DD and EDF

3.2.1 Effect of default timing and default point on EDF

Model 1 is standard KMV model with constant default point and timing. Model 2 assumes that default timing is a continuous random variable, meaning default may occur at any-point-in-time before maturity, and default point is fixed. In model 3, default timing is still a continuous random variable and default point change randomly with time.

The same trend of three curves exhibited in figure 3 illustrate that three models are consistent with each other in credit risk identification.

Two curves of model 1 in figure 3 are roughly the same, so recognition capability of model 1 is weak.In contrast, the wide volatility of Model 3 curve proves validity and higher sensitivity of modified model. Model 3 can identify credit risk better. In addition, volatility of ST Group curve in Figure 3 left is smaller than that of *Non ST Group* in Figure 3 right, which indicates that *Non ST Group* is more sensitve to changes of default timing and default point.

3.2.2 Effect of share reform on DD

Equity structure plays an important role in risk-neutral probability of default, and it is necessary to analyze effects of share reform on DD. Table 2 shows changes before and after share reform in DD of twelve stocks which achieved full circulation between 2008 and 2009.

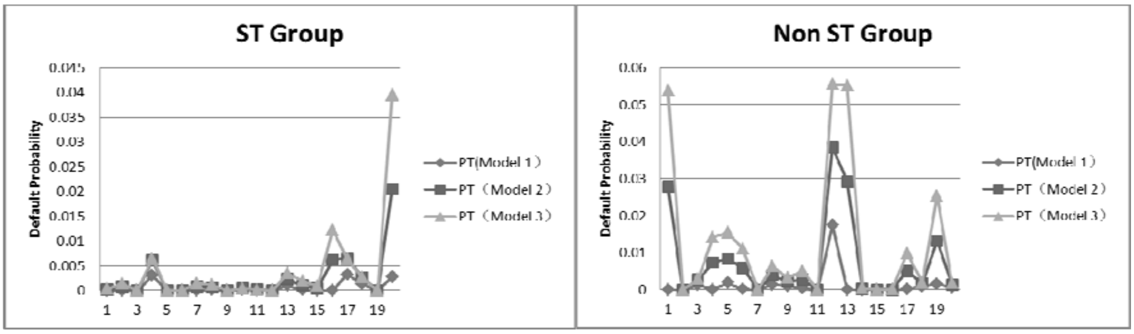

Figure 3 Effect of Default Timing (Left) and Default Point (Right)

First, Z score of single sample K-S normality test is 0.63, and its associated probability is 0.822 larger than significant level 0.05. It means DD approximately submits to normal distribution.

Second, T test shows that mean of DD increases from 2.4805 to 3.5462 after share reform and default probability decreases. DD before the share reform is positively relative to that of after the share reform. Correlation coefficient is 0.776 with a associate probability 0.006 less than significant level 0.05. Overall, share reform indeed decreases default risk of samples.

Table 2 Effect of Share Reform on DD

Stock Code	Corporate Abbreviation	DD Value	
		Before Share Reform	After Share Reform
000301	EASTERN SILK MARKET	2.688	4.290
000619	CONCH PROFILES AND SCIENCE	2.572	4.625
000635	YOUNGLIGHT CHEMICALS	1.608	1.961
000700	MOULD & PLASTIC TECHNOLOGY	1.623	2.568
000710	TIANXING INSTRUMENT AND METER	1.917	3.439
600207	ST ANCAI HI-TECH	3.158	3.229
600338	ST SUMMIT INDUSTRY	2.627	3.302
600381	ST SUNSHINY MINING	2.807	4.385
600419	ST TIANHONG PAPERMAKING	2.526	3.741
600792	ST MALONG INDUSTRY GROUP	2.197	2.806
600793	ST PAPER INDUSTRY	2.322	3.100
600847	ST WANLI GROUP	3.723	5.110

3.2.2 Effect of share reform on DD

Financial market changes rapidly, we research effects of financial environment which is measured in quity volatility on DD by Pearson correlative test. As second and third column of Table 3 shows, equity volatility is increasing from 2005 and slowed down in 2008, even fell back in 2009. Pearson test results in the fourth column illustrate that there is a significantly positive linear coefficiency between equity volatility and asset volatility from 2005 to 2009. This comovement trend is always in, especially in 2007. In contrast, correlation coefficient between equity volatility and DD is negative and decreasing year by year, and rises in 2009.

Table 3 Pearson Correlative Test

Year	Mean of σ_E	Std. of σ_E	Pearson Correlative Test between σ_E and σ_A		Pearson Correlative Test between σ_E and DD	
			Pearson correlation	P Value	Pearson correlation	P Value
2005	0.465388	0.0897	0.349	0.002	-0.782	0.000
2006	0.522389	0.10713	0.619	0.000	-0.621	0.000
2007	0.686939	0.211476	0.894	0.000	-0.521	0.000
2008	0.702539	0.122217	0.680	0.000	-0.489	0.000
2009	0.52341	0.073826	0.398	0.000	-0.579	0.000

3.3 Credit risk predictive ability analysis KMV model

3.3.1 Comparative analysis of warning effect DD and EDF

Studying on the first six *ST* companies, we find DD decreases with time close to ST year. As depicted in Figure 4, DD indicates the increasing credit risk two years before ST. By contrast, EDF doesn't change significantly. That is to say, DD is more intuitive to predict changes of default risk.

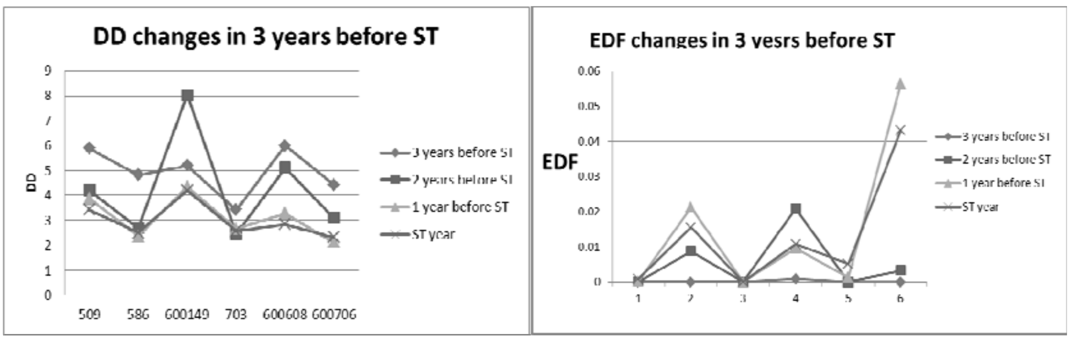

Figure 4 Comparative Analysis of Warning Effect of DD and EDF

3.3.2 Sensitivity of DD to deterioration in credit status

(1) Time series analysis

One-way ananlysis of variance in Table 4 shows that DD differs obviously in different time close to *ST* year. Multiple comparison test indicates that there is no remarkable difference between DD of two years and three years before *ST*. However, as a leading warning, DD decreased dramatically in two years before ST.

Table 4 Variance analysis-LSD Test

Time 1	Time 2	Mean Difference	Significant Level
Three years before ST	Two years before ST	0.68912	0.363
	One year before ST	1.8496	0.021
	ST year	1.9845	0.014

(2) Cross-section analysis

DD of samples is divided to nine discrete intervals, so frequency stacked picture can be plotted, where fequency is the ratio frequence in each interval of *ST Group* or *Non ST Group* accounting for total *ST* or *Non ST*. Then we plot downward cumulative frequency curve for each *ST Group* interval.

Figure 5 shows most DD of Non ST Group distribute in [5, +∞), the proportion is 19.5%, and 58.03% of Non ST Group DD is greater than three. DD of ST Group intensive area is [2, 4], the proportion is 62,43%. If we set a warning line, if DD of a sample company is less than 3, there is a possibility of 56.1% for this sample to be determined as a aggravated credit status. If it is less than 2, we would 91.9% believe credit crisis occurs in this company and what should be done is to strengthen prevention and control.

4 Empirical Study of DD-Logistic Model

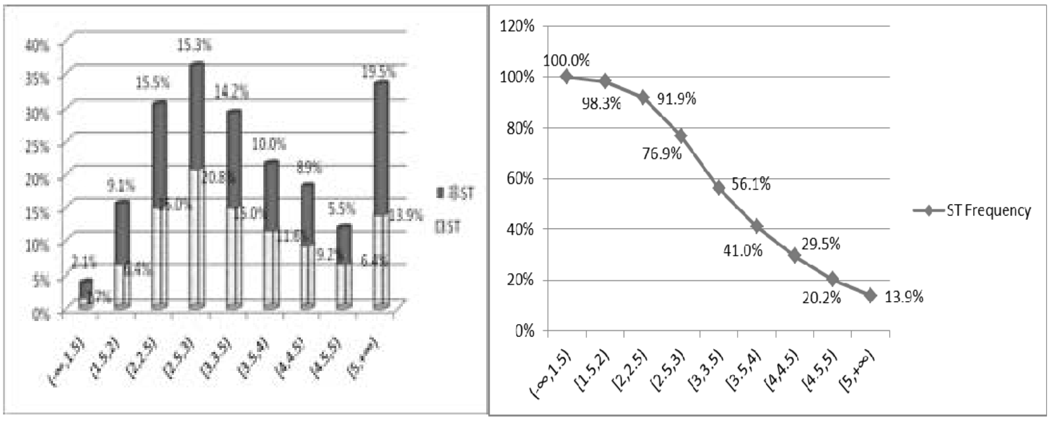

Figure 5 Frequency Stacked Picture and Cumulative Frequency Curve of DD

As previously mentioned, DD is a better indicator than EDF to reflect default risk.Now we take both financial information and market information into consideration and introduce DD to Logistic model, then analyze predictive precision of model.

4.1 Construct logistic model

Ficancial indicators reflecting credit quality are always highly dimensional and highly correlated, which dissatisfies request of no linear correlation in Logistic regression analysis, and may results in informative loss of raw data,and further reducing of reliability in parameter estimation of logistic model. In a word, default measuring model is finally meaningless. Therefore, we firstly choose eleven financial factors related to LogitP by factorial analysis, they are comprehensive strength denoted by FAC1, earning power denoted by FAC2, operation capability denoted by FAC3,development and profitablity of asset denoted by FAC4, fixed assets management capabilities denoted by FAC5, earnings management denoted by FAC6, ability of asset growth denoted by FAC7, profit ability denoted by FAC8, cash fund-raising capcity denoted by FAC9, collection capacity denoted by FAC10 and long-term solvency denoted by FAC11.These indicators can effectively measure potential credit risk in financial data. As formula 17 shows, we construct Logistic model according to financial factors of samples from 2001 to 2006, called model 1.

$$Logitp_i = \ln(\frac{p_i}{1-p_i}) = -4.4979*FAC1-11.8062*FAC2-2.7811*FAC3$$
$$+0.3539*FAC4+1.3933*FAC5+1.7545*FAC6-3.0279*FAC7+1.7724*FAC8 \quad (17)$$
$$-2.7261*FAC9-4.9953*FAC10+18.4786*FAC11$$

We make use of financial factors of 2007 and 2008 to test model 1 and predict credit risk in 2009 and 2010. Scatterplot between model output default probability and actual probability is Figure 6, where default probability of *ST Group* is one and that of *Non ST Group* is zero.

Obviously, model 1 is easy to distinguish. Predictive probability of each sample approaches to zero or one. The smaller the value is, the easier it is to be determined as *Non ST Group*, otherwise, as *ST Group*. Assuming default point is 0.5, if default probability of one *ST Group* sample is less than 0.5, it would be wrong determined as *Non ST Group*, which is called first class of false positive. On the contrary, if a Non ST Group sample with greater probability than 0.5 is determined to be *ST Group*, the second class of false positive occurs .Observing special point marked in Figure 6,default probability of *non ST Group* samples with stock code 000533 and 000665 are greater than 0.5, but unfortunately, they would be wrongly determined as *ST Group*.In fact, rate of first class false reaches up to 65% and the second class false rate is 25%, total false rate is 35.26%. There is serious Gramer Problem.[12]It shows that logistic model based on financial information is not good enough to predict default risk.

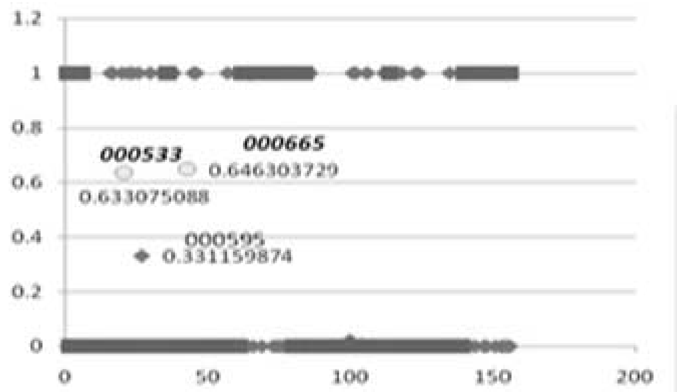

Figure 6 Scatterplot of Default Probability(♦ denotes model 1 and ■ denotes actual probability)

4.2 Construct DD-logistic model

We introduce DD to logistic model by Eviews 6.0 and construct model 2 standing for DD-Logistic model.All coefficiency pass the significant test.

$$Logitp_i = \ln(\frac{p_i}{1-p_i}) = -4.6283*FAC1-10.8191*FAC2-3.9642*FAC3$$
$$+2.2509*FAC5+2.7366*FAC6-3.6809*FAC7+3.0721*FAC8-3.3715*FAC9 \quad (18)$$
$$-9.9499*FAC10+17.0938*FAC11-0.6904*DD$$

Table 5 shows that first class false rate of model 1 is 65% which means the model is not satisfactory.However, model 2 rate of first class false positive reduces to 22.5%. So model combining financial information and market information can better control the first class false rate.

Table 5 Forecast Accuracy of ST and Non ST Group

Test Result / Model	ST Group	Non ST Group
Model 2(involves DD)	0.775	0.474
Model 1	0.35	0.75

4.3 Comparative analysis of model discriminative efficiency

4.3.1 Comparative analysis by ROC curve

We get default probability of validation samples by model 1,model 2 and KMV model and plot

ROC curve by SPSS 16.0 as Figure 7. Table 6 shows results of validity test.

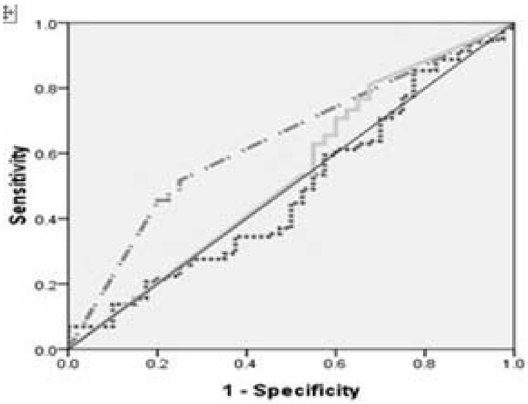

Figure 7　ROC Curve

Solid straight line is reference line, solid curve stands for Logistic model not including DD, dotted line denotes KMV model, dash and dot line represents DD-Logistic model

Table 6　Validity Test of models

Model	Area	Standard Error	Associated Probability
Model 1	0.535	0.056	0.508
KMV model	0.487	0.054	0.801
Model 2	0.637	0.049	0.010

We can conclude Model 2 distinguish credit risk best by ROC curve and vadility test[13]. The area of Model 2 reaches 0.637, associated probability 0.01 under 95% confidence interval is less than corresponding significant level 0.05. Area of Model 1 in ROC curve is greater than 0.5, which means better effect than random assumption. KMV model is the worst.

4.3.2 Comparative Analysis by CAP Curve

As depicted in Figure 8, CAP curve obtained from Model 2 is cloest to perfect curve, which means predictive effect of model 2 is best. Due to the delay,distorition and other characteristics of financial information, Model 1 works a little worse than Model 1. CAP curve of KMV model approaching to random curve is unsatisfactory. Therefore, only using KMV model to forecast credit risk of Chinese manufacturing industry may result in high false positives, which may be caused by small density of range of EDF.By taking both financial and market information into accout,DD-Logistic model is superior to KMV model and Logistic model.

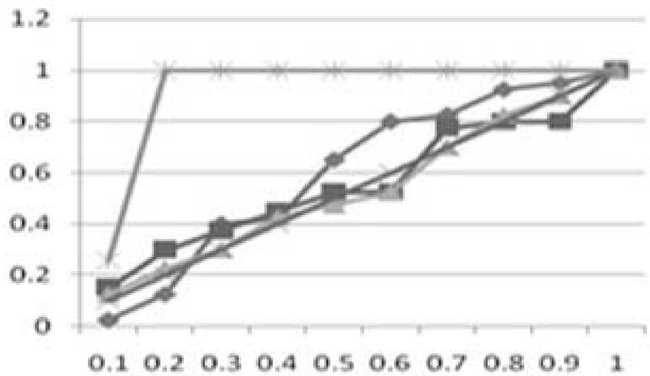

Figure 1　CAP Curve

* denotes perfect curve, ♦ is PT including DD, ■ shows PT not including DD, ▲ denotes EDF of KMV and × is random curve

5 Conclusion

First,we introduce dynamic default point and random default timing to modify KMV model.And empirical study shows that modified KMV model identifies credit risk better. Related factors analysis holds that share reform decreases default risk of samples, correlation coefficient between equity volatility and asset volatility is positive,but that between equity volatility and DD is negative. In addition, DD is a better indicator than EDF to distinguish credit ststus.

Second,comparative analysis by ROC and CAP curve concludes that DD-Logistic model has higher efficiency and precision than standard KMV model and Logistic model. Banks providing credit to their clients should consider this model.

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