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Expected Default Measures in the KMV model and the Market-based model:

Empirical evidence from Chinese listed companies

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Abstract:

Two credit risk models are applied to calculate the expected distance to default in a sample of 32 Chinese listed non-financial companies from 2006 to 2011.One is the KMV(Merton) model under the machinery of option pricing and other is the market based model relied on a conditional version of capital asset pricing model(CAPM). The results imply that both KMV model and the market based model are valid to distinguish risky firms and profitable firms. Through regression analysis on the difference of two models with the interaction effect of leverage ratio and equity volatility, this study indicates that the market based model has better ability to identify the default risk in highly leveraged firms. Also, the predictive accuracy of the adjusted KMV model is stable to the change of default points in Chinese stock market, which is different from KMV Company's existing result.

Keywords:

Default risk, Distance-to-default, KMV model, Market based Model, Capital Asset Pricing Model (CAPM), Leverage ratio, Equity volatility

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1. Introduction

Credit risk is the risk of loss due to a debtors' non-payment of a loan or other line of credit. A firm's failure to meet its financial obligations results in the default, which affects markets participant. To investors, the accuracy of these predictions is essential for their sound risk management. To institutional lenders, such as banks, the new capital adequacy framework (Basel II) requires a more active role of banks in predicting the default risk of their loan books. The need for reliable measures of credit risk is clear to all.

The modern credit risk measurement models include J.P Morgan's Credit Metrics, McKinsey's Credit Portfolio View, CreditRisk+ developed by Credit Suisse Financial Products and the KMV model. However, the former two approaches are directly based on the probability of moving from one credit quality to another, including default, within a given time horizon, which is largely related to the credit rating system. Due to the immature credit rating mechanism in China, those two models cannot be used in China yet. The same problem appears when CreditRisk + model is applied to the Chinese credit market. Due to sufficient data for estimation the key risk-driven parameter the 'default rate', the model cannot be tested in the Chinese market, either. Unlike the above models, the structural KMV model based on Merton's option theory and corporate finance theory is empirically practical to measure the Chinese listed companies' default risk. In the framework of Merton (1974), corporate debt is regarded as the difference between a riskless bond and a put option on the value of the firm's assets. The strike price equals the face value of the debt and reflects the limited liability of equity holders in the event of default.

Although many empirical studies on the application of KMV model in Chinese stock market, such as Cheng and Wu(2002), Lu,Li and Pan(2006),Cheng,Wang andWu (2010), have proved its effectiveness and warning capacity, the classical KMV model has some overwhelming drawbacks. One of them is it contains too much subjective estimation of input parameters based on accounting data. For example, the setting of the default point. Besides, for some companies whose true market value is not assessable from accounting data, the estimated default probability might be far from reality. Furthermore, the employed accounting data suffers from an infrequent updating problem and usually is released with a time lag and possible accounting manipulations. Thus, Hall and Miles (1990), Clare andPriestley (2002) and Bystrȍm(2004) have recently developed a model using only market data to compute measures of default risk. However, they apply this market based model only in banks and financial institutions.

1.1Problem discussion

The market based model and the dynamic volatilities model, differs from Merton's original model by only obtaining observable variables from the stock market. Without the need for subjective setting variables from contingent claims analysis, this model assumes that on average the market values firms correctly and relies on a conditional version of the Capital Asset Pricing Model (CAPM) to derive a measure of the variability in actual market valuations around their expected values and distance to default.

Few studies have applied the market based model to estimate default risk in the Chinese market. It would be interesting to see how the default predictions of the market based model compared with those of a standard contingent claims model. Regression analysis on the difference between the two models with the interaction effect of leverage ratio and equity volatility is the second topic. Last, whether study different settings of the default points in the KMV model lead to significant changes to the probability of default is examined.

1.2Aim and purpose

In this study, both the KMV model and the market based model are applied to 32 Chinese listed non-financial companies covering utilities, properties, conglomerates, industrials and commerce sectors from 2006 to 2011. Three different default points are set to test the sensitivity of the default probability. The purpose of this paper is to further apply the KMV model with adjusted parameters and initially introduce the market based default calculation to the Chinese stock market. Through comparing the annual default measures from the two models, this paper aims to find a more effective approach to estimate the default risk in the Chinese stock market.

1.3Limitation

Due to lack of historical statistical data in china's credit system, this study focus as on the default distance instead of the actual default rate or expected default frequency. Besides, because of data availability, a selected sample of 32 listed companies is included in this study.

1.4Disposition

The structure of the paper is divided as follows. The introduction chapter explains the background of the subject at hand. Chapter 2 presents the theoretical background of the two models and previous empirical findings. Chapter 3 explains the methodology and Chapter 4 describes the data and examines the parameters setting. The empirical results and discussion appear in chapter 5. Finally, chapter 6 concludes the paper and

gives direction for further research.

2. Theoretical Background

This part contains a theoretical review on both the KMV model under the framework of Merton (1974) contingent claims and the market based model relied on a conditional version of capital asset pricing model for expected default measurement, followed by the empirical reviews of those two approaches for credit risk prediction.

2.1Structural credit risk models

The existing literatures that describe default process in credit risk can be divided into two primary types of models: structural models and reduced form models.Structured models, also known as contingent claims framework or option pricing approach, determine the time of default through evolution of firm's economic and financial conditions. Thus, defaults are endogenously generated and pricing the credit risk is directly linked with the value of the firm relative to a credit-event-triggering threshold or barrier. The structural approach starts from Merton (1974) who considers the valuation of risky debt with the seminal work of Black and Scholes (1973). In his model, the firm's value is simply a European call option and thus implies the default can only happen at the maturity. Extending Merton's model to a first passage model, Black and Cox (1976) specifies default as the first time the firm's asset value falls to a trigger value and allows the default to occur at any time. With this framework, Longstaff and Schewartz (1995) introduce that interest rate follows a mean reverting stochastic proves and that there are deviations from strict absolute priority into a two factor model. Leland and Toft (1996) further assume that the debt has finite life and incorporate the optimal capital structure relative to the impact of taxes and bankruptcy cost in analysis corporate debt value. Their barrier option model defines endogenously the bankruptcy threshold. Ericsson and Reneby (1988) demonstrate the finite maturity coupon securities with bankruptcy cost, corporate taxes and deviations from the absolute priority rule. Collin-Dufresne and Goldstein (2001) extend the Longstaff and Schewartz (1995) model by introducing a stationary leverage ratio of a firm.

Different from structural models, reduced form models assume a firm's default time is inaccessible or unpredictable and driven by a default intensity that is a function of state variables. The parameters governing the default hazard rate are inferred from market data and financial ratios provide a significant indication of the likelihood of financial distress, such as Altman's Z-score (Altman 2002). In this regard, the defaults and recovery rates are exogenously modeled in reduced form models while default is generated within the structure model. Thus, the structural approach has the advantage of better communication among loans' obligors, credit analysts and credit portfolio managers in terms of understandable economic variables. Also, the treatment of recovery rate in reduced form models is exogenously specified whereas in the structure models recovery rates are determined by the value of the firm's assets and liabilities at default.

2.2The standard Merton option Model

The literature on structural credit risk models was initiated by Merton (1974), who applies Black and Scholes (1973) option pricing model, to value corporate liabilities. The two main assumptions Merton adopts are 1).the firm's value is the sum of the equity and debt value. 2).the value of the firm is independent of company's capital structure, which implies the inexistence of transaction costs, bankruptcy costs, taxes or asymmetric information. In other words, the firm's capital structure is assumed to be composed by equity and a zero-coupon bond with maturity T and face value of debt D, whose values at time t are donated by E_t and $Z_{(t,T)}$ respectively, for $0 \leq t \leq T$.

Under these assumptions, the firm's asset value V_t follows a geometric Brownian motion under risk neutral probability space described by

$$dV_t = rV_t dt + \sigma_v V_t dW_t \tag{1}$$

where σ_v is the company's asset volatility and dW_t is a Wiener process under the risk-neutral probability measure.

$$V_t = E_t + Z_{(t,T)} \tag{2}$$

If at maturity T, the firm's asset value, V_T is higher than the face value of its debt, D, the firm doesn't default. The shareholders receive V_T-D and the bondholders receive D. Otherwise, if V_T<D, the firm defaults and the bondholder take over the firm from the shareholders which receive nothing. There is one restriction that the firm can only default at maturity.

The payoff to the shareholders and bondholders at time T under assumption are max $\{V_T\text{-D}, 0\}$ and $V_T - E_t$ respectively. And equity value at time t ($0 \leq t \leq T$), E_t, is defined by a European call option on the asset of the firm, with maturity T and exercise price D.

$$E_t(V_t, \sigma_v, \mathrm{T-t}) = e^{-r(T-t)}\left[e^{r(T-t)}V_t\emptyset(d_1) - D\emptyset(d_2)\right] \tag{3}$$

Where$\emptyset(.)$ is the standard normal distribution function and d_1 and d_2 are driven by

$$d_1 = \frac{In\left(\frac{e^{r(T-t)}V_t}{D}\right) + \frac{1}{2}\sigma_{v(T-t)}^2}{\sigma_v\sqrt{T-t}} \tag{4}$$

$$d_2 = d_1 - \sigma_v\sqrt{T-t} \tag{5}$$

The probability of default at time T is given by

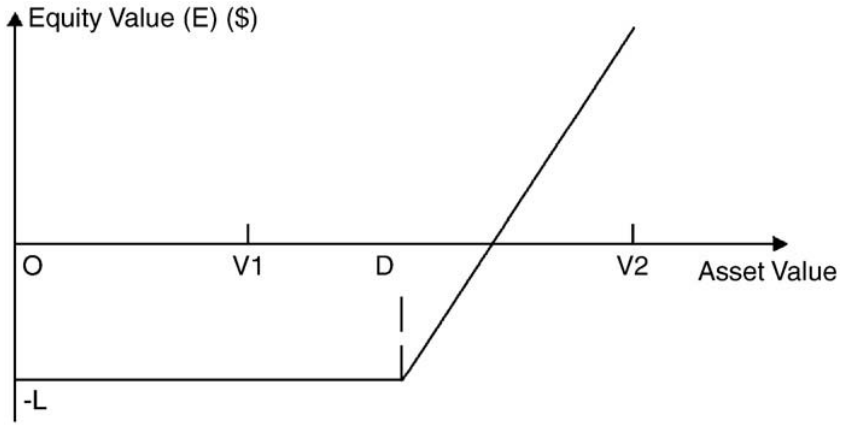
$$P[V_T < D] = \emptyset(d_2) \tag{6}$$

Like any European type option pricing model, the key parameters of Merton's model are firm's asset value V_T, its volatilityσ_v, and the face value of debt D. Although Merton's model allows to directly apply the Black and Scholes options pricing theory for the ease of implementation, it focuses on default at maturity only and does not allow for real-would consideration, such as cash constraints or liquidity problems that may cause involuntary, early bankruptcy.

2.3Implement of the Merton's model: the KMV Model

A version of the Merton model has been adapted by Vasicek (1984) and has been applied by KMV Corporation. KMV model assumes that the company will default when the company's asset value is less than the liability. And it considers the value of equity as a call option, which regards asset value as the underlying asset and the debt value as the strike price. As Figure 1 shows, L represents the shareholders' initial investment in the company; D denotes the debts in default point. When the asset value Vis more than the debt D, shareholders still gain net profits after paying debts, which is shown as an increasing equity value. The shareholders won't choose default and the call option is exercised; when the asset value is less than the debt, shareholders transfer the total assets to creditors, which is consistent with a constant equity value. They will default and the call option isn't exercised.

Figure 1 The relationship between equity value and asset value
(Source: Moody's KMV modeling default risk)



The firm's assets value V_t is assumed to follow a standard geometric Brownian motion, i.e.:

$$V_t = V_0 \exp\left\{\left(\mu - \frac{\sigma^2}{2}\right) t + \sigma\sqrt{t}W_t\right\} \tag{7}$$

With W_t~N (0, 1), μ and σ^2 being respectively the mean and variance of the instantaneous rate of return on the assets of the firm, V_t is distributed with expected value at time t, E $(V_t) = V_0 \exp\{\mu t\}$.

2.3.1 Distance to default

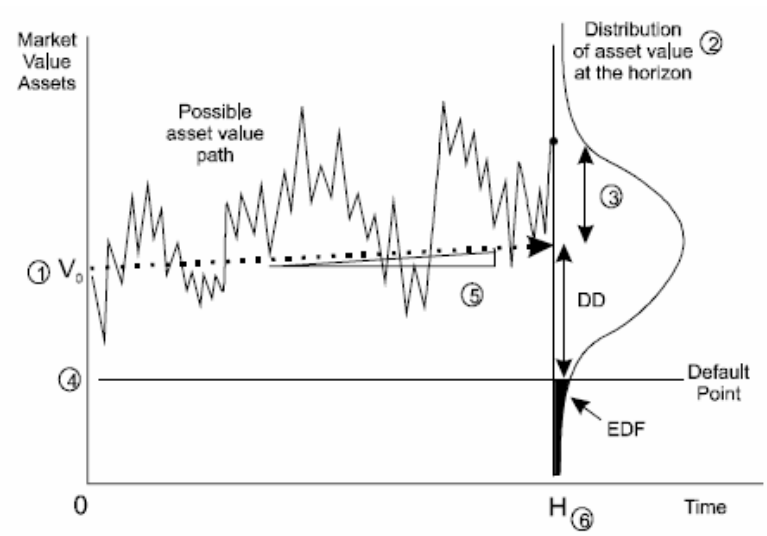
KMV implements an intermediate phase before computing the probabilities of default, which is called 'Distance-to-Default' (DD) .DD (Figure 2) is the number of standard deviations between the mean of the distribution of the asset value and a critical threshold, the 'default point' (DPT). The DPT is defined in Crosbie(2003) as half the long-term debt(LTD) plus the par value of current liabilities including short-term debt(STD), which is an attempt to capture the idea that short-term debt requires a repayment of the principle soon whereas long-term debt requires only coupon payments to be met.

The measure for distance to default is defined as follow:

$$\mathrm{DD} = \frac{\ln\left(\frac{V_0}{DPT}\right)+(\mu-\frac{\sigma^2}{2})T}{\sigma\sqrt{T}} = \frac{E(V_T - DPT_T)}{\sigma\sqrt{T}} \tag{8}$$

Where V_0 is the current market value of assets, $\mathrm{DPT_T}$ is the default point at time horizon T, μ is the expected net return on assets and σ is the annualized asset volatility.

Figure 2 KMV Model's Illustration for Default
(Source: Moody's KMV modeling default risk)



2.3.2 Uncertainty in application of KMV model

In Merton's model this distance could be negative, but for $V_t = \mathrm{DPT_T}$, it is 0. This measure is fairly parsimonious and whether this is a good model for default would then look at how well DD has historically predicted defaults. The accurate estimate of the default probability would depend on the default frequency, which would produce

an empirical curve. While the philosophy of applying an empirically estimated connection between distance to default and default probability is clear; in practice, there are a number of uncertainties, including:

- Which option model is preferred? A firm's balance sheet is far more complicated than is assumed in Merton model or the Black-Cox model in empirical studies.
- How to define the default point and measure actual liability? It is difficult to model the exactly occurred point which triggers the default. Besides, the potential liability off-balance sheet is hard to obtain either.
- Is accounting data sufficient to provide the real value of companies? It contains subjective estimation of the input parameters.

2.4 The market's view on the default measure

Stock prices go up when investors become more optimistic about the further corporate profits, which reduces the expected probability of default. On the other hand, if the market is able to value the firm correctly, it requires higher returns from high risky firms compared with low risky firms. The relative risk associated with each firm should be reflected in the price of its common stock. The market based model assumes that on average the market values firm correctly and relies on a conditional version of the Capital Asset Pricing Model (CAPM) to derive a measure of the variability in actual market valuations around their expected values as distance to default.

2.4.1 Capital Asset Pricing Model

Assume that the market values firms efficiently then the share price of any stock is given by:

$$S_{it} = \frac{\sum_{j=1}^{n} P_{jt} X_{jt}}{N} \tag{9}$$

Where S_{it} is the price of stock I at time t; P_{jt} is the price of stock i's asset or liability j at time t; x_{jt} is asset/liability j at time t; and N is the number of ordinary shares in stock i.

The measure of probability of failure is based on a conditional version of the Sharpe (1964) and Lintner (1965) Capital Asset Pricing Model (CAPM). According to the CAPM, for each stock, R_{it}, the expected return on any risky asset will be equal to the risk free rate of interest plus a risk premium. The risk premium is the sum of all systematic components of risk with the market since only nondiversifiable risk is priced in the market.

$$\mathrm{E}(R_{it}) = \beta_{it} E(R_{mt}) + RF_t \tag{10}$$

Where $E(R_{it})$ is the expected excess return on stock i at time t, $E(\frac{S_{it}-S_{it-1}}{S_{it-1}})$, β_{it} is the conditional CAPM beta coefficient on stock i at time t and $E(R_{mt},)$ is the expected excess return on the market at time t.

The actual excess return on stock i should plus a stochastic error term, υ_{it}, which on average is equal to zero.

$$R_{it} = \beta_{it} E(R_{mt}) + RF_t + v_{it} \tag{11}$$

2.4.2Measure of distance to default

The expected value of firm capital can be expressed as

$$\mathrm{E}(S_{it}N) = S_{it-1}N(1 + \beta_{it}\mathrm{E}(R_{mt}) + \mathrm{R}F_t) \tag{12}$$

And the actual value of firm capital as depending on the random term υ_{it}

$$S_{it}N = \mathrm{S}_{it-1}N(1 + \beta_{it}\mathrm{E}(R_{mt}) + \mathrm{R}F_t + v_{it}) \tag{13}$$

Therefore, the difference between the actual and expected value of a firm's capital at time t can be expressed as

$$S_{it}N - E(S_{it}N) = S_{it-1}Nv_{it} \tag{14}$$

And the conditional variance of firm capital at t-1 can be written as $(\mathrm{S}_{it-1}\mathrm{N})^2\sigma^2_{\upsilon_{it}}$, which represents the degree to which the market value of a firm's capital varies around the market's expectation of that value.

If the markets are efficient, the value of the firm at time t-1 divided to its standard deviation yields a simple measure of probability that a firm defaults, which is

$$\frac{S_{it-1}Nv_{it}}{S_{it-1}N\sigma v_{it}} = \frac{1}{\sigma v_{it}} \tag{15}$$

Thus, the larger standard deviations of the firm's capital, the smaller the probability of default; lower values of $\frac{1}{\sigma_{\upsilon_{it}}}$ imply a higher probability of firm failure.

2.5 Literature review

2.5.1 Previous studies on KMV model

Western scholars, such as Kurbat and Korablev (2002), Crodbie and Bohn (2003), Cram and Lundstedt (2004).ect, did a lot of work of demonstrating the validity of KMV model. In comparison with accounting based models, for example, Altman's Z-score and Ohlson's O-Score model, they point out the preference and effectiveness of KMV models in dealing with credit default. In 2004, the "New Basel Capital Accord" also recommended the Internal Rating Based Approach (IRB) to manage

credit risk and appealed to KMV model when applying IRB. However, Bharth and Shumway (2005) examine the accuracy of the default forecasting in KMV model and how realistic its assumptions are. They find that most researchers applying KMV model without knowing much on the statistical properties and suggest a model with better predictive properties during the maturity period be improved.

Chinese empirical studies on KMV model have been focused since 2002. Cheng, Wu(2002,sample size 15) ,Ye,et(2005, sample size 22), Lu,Li,Pan(2006, sample size 5) adjust the parameters of traditional KMV models and find that the mortified KMV model can timely identify and forecast the default risk of Chinese listed companies. Meanwhile, some scholars applied KMV model to one or several industries and show that the KMV model can diversify default risk for different industries. Zhou (2009) introduced the KMV model to test credit risk for insurance industry in China. Zhang,Li,Wang(2010) compare with 10 Chinese listed companies in Logistics with USA ones during financial crisis and demonstrate its effectiveness of measuring credit risk. Huang,Sheng,Li(2010) evaluate of default risk based on KMV model for the three national commercial banks (ICBC,CCB and BOC) and also reach the same conclusion. However, all of their sample are not big enough or cover most industries.

Although previous studies have shown that KMV model is an effective tool and guidance for quantitative credit risk in China, some existing works have further discussed the modified parameters and its relationship with default probability. One of those controversial parameters is the default point. Huang,He(2010) study on probing default point of KMV in 5 listed Chinese banks(CMBC, CMB, SDB, SPDB, HUA XIA BANK) and find that the model of default point differs according to different banks. However, Cheng,Wang and Wu (2010) develop a novel model based on the original KMV model with tunable parameters to measure the credit risk of Chinese listed small and medium enterprise and point out that the predictive accuracy of adjusted KMV model is stable to the change of default points. Another studied area is the relationship between asset size and default. According to Moody company's research and Cheng,Wang andWu (2010), the asset size plays an important role in measuring default.

In the following study, two matched samples are selected in accordance with the similar asset size (market value) in order to minimize the effect of asset size while measuring default to the change of different default points.

2.5.2 Recent research on market based model

In contrast to structured models which partly rely on past accounting information, Hall and Miles (1990) originally develop an alternative approach of bank failure estimation purely using stock market information. It is different to assess the risk of value of assets and liabilities for banks and financial institutions. They instead focus on share price, according to the capital asset pricing model (CAPM), to estimate the

market perception of volatility of financial institutions' underlying portfolio. Another advantage of his new method is to reduce the impact of a considerable time lag and thus enhances the indication of the likelihood of firm failure in the future.

Clare(1995) follow the spirit of Hall and Miles (1990), employ stock prices and stock volatility as a measure of distance to default for security houses in the UK. Later, Clare and Priestley (2002) find an increase default probability of commercial banks in Norway after the financial deregulation in the mid 1980 and the trend continues until the crisis in 1991. Since then, regulators and researchers pay attention to assess these measures of default probability as systemic risk. Bystrȍm(2003) also employed Hall and Miles (1990) method to study the probability of financial institution failure in Swedish banking sector during the 1990 and find a close correspondence between changes in the estimated default probabilities and the actual credit event occurring.

Recently, Tabak and Luduvice,ect (2011) derives the estimated default probabilities for 30 different economic sectors in Brazilian stock market following the approach of Bystrȍm(2004). They find that the estimated default probabilities for different sectors show common trends and suggest that the macro-financial variables be determinants of default probabilities. However, the major drawback of this market based approach is its purely statistical nature and lack of theoretical grounds. In addition, there is no natural way of transforming these signals to actual default probabilities.

3. Methodology

This section contains a presentation of how the distance to default measures are obtained from KMV model and market based model.

3.1KMV modeling

First, derived from (3), the equity value (E) is a function of asset value (V), default point (D), asset value volatility (σ_V), risk free rate(r) and debt maturity (T), which is expressed as

$$E = V\emptyset(d_1) - De^{-rT}\emptyset(d_2) = f(V, \sigma_v, r, D, T) \tag{16}$$

Where$\emptyset(.)$ is the standard normal distribution function and d_1 and d_2 follow (4), (5).

Second, set up the estimation of asset value and asset volatility from observed equity prices by introducing the relationship between the equity value volatility (σ_E) and the asset value volatility (σ_V),

$$\sigma_E = \frac{V\emptyset(d_1)}{E}\sigma_v = \mathrm{g}(\mathrm{V}, \sigma_v, \mathrm{r}, \mathrm{D}, \mathrm{T}) \tag{17}$$

Third, solve the two unknown parameters (V,σ_V) in (18) through Newton-iterative method.

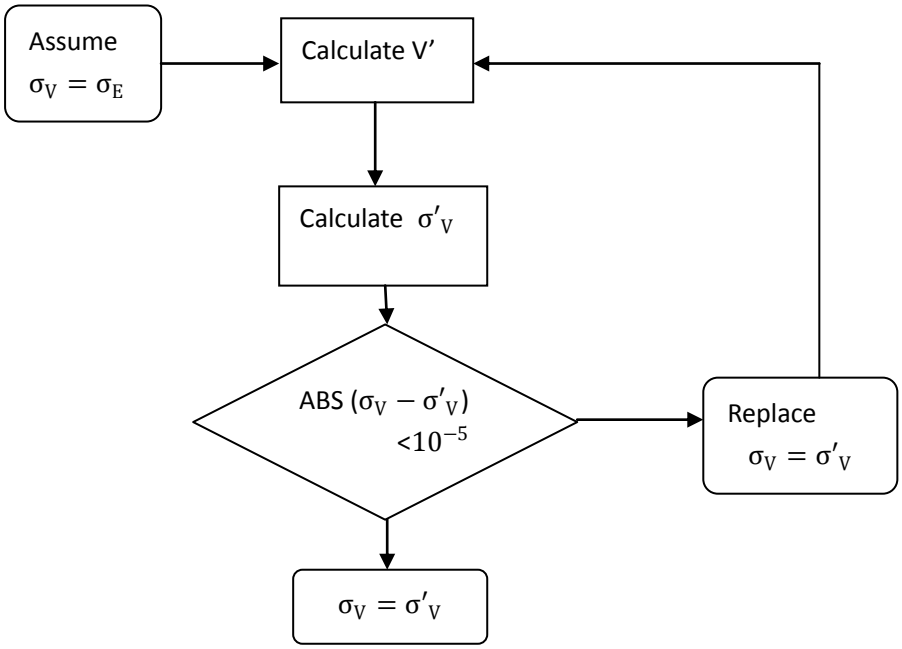
$$\begin{cases} f(\mathrm{V}, \sigma_\mathrm{V}) - \mathrm{E} = 0 & (18a) \\ \mathrm{g}(\mathrm{V}, \sigma_\mathrm{V}) - \sigma_\mathrm{V} = 0 & (18b) \end{cases}$$

The process of Newton-iterative Method is illustrated in Figure 3. The Newton-iterative Method initially assumes the asset volatility equals to the equity volatility and input into (18a) to calculate the asset value, V'. Input V' into (18b) to recalculate a new asset value volatility, σ'_V. Loop the above calculation until the difference of asset value volatility, σ'_V and assumed true asset value volatility σ_V is less than 10^{-5}. Then obtain the estimated asset value volatility and asset value. The Newton-iterative of V and σ_V can be carried out by executing a problem in MATLAB 7.0. The program is detailed in Appendix III.

Last, input all the variables, asset value (V), default point (D), asset value volatility (σ_V), risk free rate(r) and debt maturity (T,)to calculate the measure of distance to default of each company through

$$\mathrm{DD} = \frac{\ln\left(\frac{v_0}{DPT}\right) + (\mu - \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} = \frac{E(V_T - DPT_T)}{\sigma\sqrt{T}} \tag{8}$$

Figure 3: The Newton-iterative Method



3.2Market-based modeling

3.2.1The conditional CAPM

The (11) presents the risk premium for stock i where the expected return on market portfolio is a function of its own expected variance if only non-diversifiable risk is compensated for in the market.

$$E(R_{mt})=\lambda_t E(\sigma_{mt}^2) \tag{19}$$

Where λ_t is the market price of risk; σ_{mt}^2 is the conditional variance of the excess return on the market portfolio.

Since the above is only correct on average, the actual excess return on the market should plus a stochastic error term, ε_{mt}, which on average is equal to zero.

$$R_{mt} =\lambda_t E(\sigma_{mt}^2),+\varepsilon_{mt} \tag{20}$$

The conditional variance of the market portfolio around its expected value is:

$$E(\sigma_{mt}^2)=E(\varepsilon_{mt}^2) \tag{21}$$

Thus insert (21) into (20),

$$R_{mt} =\lambda_t E(\varepsilon_{mt}^2)+ \varepsilon_{mt} \tag{22}$$

Substituting (22) into (11) with $\beta = \mathrm{Cov}(R_{it}, R_{mt})/\sigma_{mt}^2$ and $E(\mathrm{Cov}(R_{it}, R_{mt})) = E(\varepsilon_{mt}, \upsilon_{it})$, the excess return on stock i can be rewritten as

$$R_{it} =\lambda_t\ E(\varepsilon_{mt}, \upsilon_{it})\ \ +RF_t+\upsilon_{it} \tag{23}$$

,which implies the stock return depends on the time-varying market price of risk, λ_t, scaled by time-varying conditional covariance between the excess return on stock i and the excess return on the market portfolio.

3.2.3 Estimation in Bivariate GARCH-M model

In order to obtain the υ_{it} ,a bivariate Generalised Autoregressive Conditional Heteroscedaticity In Mean (GARCH-M) model is applied. Unlike the restrict non-standard versions of ARCH and GARCH Hall and Miles (1990) use and a non-standard bivariate AGARCH-M model Clare and Priestley (2002) develop, this study follow Bystrȍm(2003) to model the conditional CAPM under a bivariate GARCH-M framework.

It is true that the choice of GARCH specification is rather parsimonious and neglects the possible asymmetries in the return series, but the advantage is that it only contains 10 parameters to estimate for each sample company. The estimation system is shown as following.

$$R_{it} = RF_t, + \lambda_t \; E\left(\sigma_{\upsilon_{it}} \; , \varepsilon_{mt}\right) + \upsilon_{it} \tag{24}$$

$$R_{mt} \; = RF_t + \lambda_t E\left(\sigma^2_{\varepsilon_{mt}}\right) + \varepsilon_{mt} \tag{25}$$

$$\mathrm{E}\left(\sigma^2_{\mathrm{v}_{\mathrm{it}}}\right) = \emptyset_{\mathrm{i},1} + \emptyset_{\mathrm{i},2}\upsilon^2_{\mathrm{it}-1} + \emptyset_{\mathrm{i},3}\sigma^2_{\upsilon_{\mathrm{it}-1}} \tag{26}$$

$$\mathrm{E}\left(\sigma^2_{\varepsilon_{mt}}\right) = \emptyset_{m,1} + \emptyset_{m,2}\varepsilon^2_{mt-1} + \emptyset_{m,3}\sigma^2_{\varepsilon_{mt-1}} \tag{27}$$

$$\mathrm{E}\left(\sigma_{\upsilon_{it}}, \varepsilon_{mt}\right) = \rho_{v,\varepsilon}\sqrt{E(\sigma^2_{v_{it}})E(\sigma^2_{\varepsilon_{mt}})} \tag{28}$$

Where $\mathrm{E}\left(\sigma_{\upsilon_{\mathrm{it}}}{}^2\right), \mathrm{E}\left(\sigma_{\varepsilon_{\mathrm{mt}}}{}^2\right)$are the expected conditional variances of υ_t andε_t, $\rho_{\upsilon,\varepsilon}$ is the correlation coefficient, $\mathrm{E}(\sigma_{\upsilon_{\mathrm{it}}}, \varepsilon_{\mathrm{mt}})$ is the expected covariance between υ_t and ε_t.

First, estimate each equations by ordinary least squares (OLS) for (24), (25) without any uncertainty measures to test the presence of ARCH effect by a Ljung-Box test. Second, estimate each equation by GARCH(1,1) for (24), (25) and declare coefficient vectors to use in bivariate GARCH-M model. Third, set up the value of variance-covariance matrix using the values of coefficient vectors according to (26), (27). Forth, estimate by maximizing the log-likelihood function for (24), (25) and (28).All estimations for each 32 companies are obtained manually in a bivirate GARCH-M model with LogL object in EVIEWS 7.0 software package. The code is detailed in the Appendix IV.

From the above equations, the estimation of $\sigma_{\upsilon_{it}}$, the conditional standard deviation of the individual company's excess return at each point in time is obtained. Then transform into the measure of default value, $\frac{1}{\sigma_{\upsilon_{it}}}$.

This study chooses monthly data to calculate the probability of failure within the next month. To create a yearly default measure from the monthly $\sigma_{\upsilon_{it}}$, 12 monthly variances within one year are added up as

$$\frac{1}{\sqrt{\sigma_{v_{i1}}^2+\sigma_{v_{i2}}^2+\cdots+\sigma_{v_{i2}}^2}} \tag{29}$$

4. Data

This section presents the data used for the calculation and the selection process for a certain listed companies in the study, as well as the setting of parameters in both KMV model and market based model.

4.1 Data window

The data window is from 2006-01-01 to 2011-12-31. Prior to china's split share structure reform executed in 2006, domestic A shares were divided into two classes, the tradable shares which can be freely brought and sold by normal investors; and non-tradable shares. The value of non-tradable shares is hard to estimate. If the price of non-tradable shares is simply represented by the price of per share price, the company's equity value will be overestimated. Thus, this study chooses the data window after the share structure reform which cancelled the division of shares in all listed companies. Classified as frequency, the datum consist of daily datum from 2006-01-01 to 2011-12-31, including stock price, market value, risk free rate and market return index; and annual datum from 2006 to 2011, including risk free rate ,current liability and long-term liability.

4.2 Sampled companies selection

In order to investigate the two models' measure on credit risk accurately, various factors, such as industry sector, companies' asset size and operation performance, are taken into account to make the sample selection decision. 16 special treatment (ST&*ST) companies and 16 matched blue-chip companies are selected from listed Chinese stock market under the following steps:

a) Select the ST&*ST companies covering all the industry except finance industry. The ST companies are those being special treated because of negative net profit in two consecutive years and *ST are those suffering from losses for three consecutive years. Yet they should be still listed in Shanghai and Shenzhen Stock Exchange during the whole data window, which ensures there is no missing data. They are assumed to be more risky due to the worse operation performance.
b) Find the matched blue-chip companies. Blue-chip companies are those who have the best performance and the most average annually earning per share (fully diluted) in each industry among the non-ST&*ST companies. They are assumed to be less risky because of the above average operation performance.

The entire datum is from CSMAR Solution Database. The information of the years in which company became ST/*ST is obtained from fiance.ifeng.com. A list of 32 sample companies is detailed in Appendix I.

4.3 Parameter setting

a) The equality value (E)

The equality value is equal to the annual market value of equity. Since this study chooses the data window after 2006 in which china's split share reform took effect, it doesn't contain any further calculation with classification of sharable equity value and non-shareable equity value. Data is obtained directly from CSMAR Solution Database.

b) The volatility of equity value (σ_E)

The volatility of equity value is calculated by the historical daily equity return data. Under the assumption that the stock price follows the Geometric Brownian Motion, log return is preferred. Thus the volatility of equity value is expressed as

$$\sigma_E = \frac{\frac{1}{t-1}\sum(u_i - \bar{u})^2}{\sqrt{\frac{1}{n}}} \tag{30}$$

$$u_i = \text{In}\frac{S_i}{S_{i-1}} \tag{31}$$

Where u_t denotes the log return at time t;S_t denotes the stock price at time t; n is the trading day, which is approximately equal to 250 days. Excel software is use for the above calculation.

c) The Debt (D)

The short-term debt (STD) plus the long-term debt (LTD) is the total liability. Those accounting data are obtained from annual report provided in CSMAR Solution Database.

d) The default point (DPT)

When the company defaults, the asset value is generally between the current liabilities and the book value of total liabilities, which can be described to:

Default point = current liabilities + k × long-term liability

Where $0 \leq k \leq 1$

According to KMV Company, the most frequent default point is at k=0.5 and the predictive accuracy of model is sensitive to the changes of default point. However, this default point is empirically based on American companies, which may be different in Chinese situation. Thus, this study set three default points, k=0.5 (DD0), k=0 (DD1), and k=1 (DD2), in order to discuss and compare the effectiveness of credit risk in the three sceneries.

e) The liability maturity (T)

It is impossible to gain the detail of maturity time, this study assume the liability maturity time is one year.

f) Risk-free rate (r)

Since china doesn't have the real risk-free rate, this study apply one-year time deposit rate issued by the People's Bank of China. When analyzing one-year's data, this study use the r issued at the beginning of the next year.

g) Monthly excess stock return(R_{it})

The daily excess stock return can be obtained in $E(\frac{S_{it}-S_{it-1}}{S_{it-1}})$ where S_{it}presents daily stock price. This study applies the daily log return $u_i = \text{In}\frac{S_i}{S_{i-1}}$, then average the daily excess stock return into monthly excess stock return.Excel software is use for the above calculation.

h) Monthly market return (R_{mt})

The monthly market return is downloaded from CSMAR Solution Database directly. It is calculated on equal-weighted average method without consideration the monthly cash dividend.

i) Monthly risk-free rate(RF_t)

The monthly market return is downloaded from CSMAR Solution Database directly, which transfers the annual risk free interest rate into monthly data based on the compound interest calculation method.

5. Results and Analysis

This section addresses the results of expected default measures with the sensitivity analysis of default points to the change of default measures and models validation analysis. Through regression analysis in term of leverage ratio and equity volatility, the difference of two models in default prediction power is further discussed.

The value of default to distance in different default points from KMV model is shown in Appendix II. The daily data described in market based model show typical characteristics for stock return series, such as heteroscedasticity and excess kurtosis. The Bivatiate GARCH-M model is applied to each of 32 companies and all GARCH parameters are positive. The average unconditional correlation between the ST&*ST companies and market return is higher than that between blue chip companies and market return, which is consistent with the assumption that ST&*ST companies have more severe risk issue. The final outcome of default measure from market based model is shown in Appendix II.

5.1 Comparison with three default points in KMV

The most frequently occurred default point from KMV Corporation is at the point when the value of the company is 50% greater than or equal to current liability and the prediction accuracy is sensitive to changes of the point. However, in Chinese stock market, the company's structure is different from that of American market. In order to examine the influence of different default points on the recognition ability of credit risk, three situations are discussed:

1) DD0: Current liabilities+0.5×Long-term liabilities,
2) DD1: Current liabilities,
3) DD2: Current liabilities+ Long-term liabilities.

5.1.1 Statistical tests on three default points

All the default distance value of 32 sample companies are collected from 2006 to 2011.The total observations for default distance at each default point is 192. The summary statistics description of three default distance is shown in Table 1.

One of the credit risk evaluation criteria is to spread out the results of default distance as far as possible.The bigger the difference of distance to default is, the more sensitive to distinguish the credit risk. According to statistical theory, it can be more sensitive to reflect the difference by using their variance. With the bigger variance, the sample has bigger difference. To this regard, the variance of all samples calculated with DD2: Current liabilities+ Long-term liabilities is bigger than that calculated with DD0: Current liabilities+0.5×Long-term liabilities or DD1: Current liabilities. Thus, the

amended KMV with total liabilities as default point is more sensitive to distinguish the credit risk of the sample companies.

Table 1 Statistic description of default distance at three default points

	DD0	DD1	DD2
Mean	1.0303	1.0627	0.99032
Variance	0.988137	0.965789	**1.041809**
Median	1.2588	1.274	1.2335
Kurtosis	-0.27347	-0.61803	0.30516
Skewness	0.042353	0.11951	-0.07825
Maximum	3.8839	3.8839	3.8839
Minimum	-2.0613	-1.655	-2.9116

However, for more accurate statistic analysis, F-variance tests, T-tests and Wilcoxon-tests are applied to compare the variance, mean and median values between each two values of default distance in Gretl.

Table 2 Statistic tests of default distance at three default points

	F-test		T-test		W-test	
	F	P-value	T	P-value	Z	P-value
DD0,DD1	1.02314	0.8764	-0.32199	0.7476	-0.54159	0.5881
DD0,DD2	1.05432	0.7151	0.388046	0.6982	0.55079	0.58178
DD1,DD2	1.07871	0.6011	0.707852	0.4795	1.0271	0.30437

Note: All P-values is two tailed.

Null hypothesis (F-test): Difference of variance equals to zero.

Null hypothesis (T-test): Difference of means equals to zero.

Null hypothesis (Wilcoxon-test): Two medians are equal.

As Table 2shows, none of the above tests show statistic significant at 95% confidence interval level since all the P-values are above 0.05. Therefore all null hypotheses are not rejected. There is no significant difference in the variance, mean and median values between each two values of default distance. By comparing the test results, the applicability in distinguishing the credit risk of default distance with three adjusted KMV models is examined. In contrast to the result of KMV Company that the predication accuracy of KMV model is sensitive to the changes of different default points, this study concludes the stability of default distance to the changes of default points in Chinese stock market.

5.1.2 Stability of default distance to changes of default points

According to KMV Company, the value range of default point is between the current liabilities and the total liabilities. The idea of this definition is that short-term debt requires a payment soon whereas long-term debt can be paid off once the coupon

payments are met. The most recommended default point is current liabilities plus 50% of the long-term liabilities, as DD0 follows. Although this default point has been proved empirically in KMV Company's existing result, the framework of this setting default barrier is questionable in several ways.

First, it doesn't take the liquidity asset into consideration. The trigger of default is complicated to determine. The default could occur when there is no liquid asset left and the free cash flow becomes zero. The factor of default barrier cannot simply rely on the accounting reports either, considering the possible accounting manipulation problems. What is more, the sensitivity of default distance value to the changes of default points largely depends on the ratio of current liability and long-term liability, which is closely related to the company's financing preference.

In addition to focusing on liability structure in determining the default barrier, empirical findings, such as Collin-Dufrene and Goldstein (2001), Hui,Lo and Huang(2002), suggest a stationary leverage ratio for modeling the default risk and document that the leverage ratio is the natural alternative for an early warning signal. The impact of leverage changes on default measure will be discussed later.

In the above sampled companies, the mean and standard deviation of total 192 observations' ratio of current liability and long-term liability are 0.88133707, 0.165512813 respectively. It implies that both the Blue Chip and ST&*ST companies in Chinese stock market much prefer to short-term debt and thus results in the little difference among three default points. This interesting phenomenon is not hard to understand. Blue chip companies tend to short-term financing in the sake of current liquidity issue while ST&*ST companies have difficulty in long-term debt due to their worse operating and financial situation. Thus, it is mainly the high ratio of current liability in total liability that results in the stability of default distance to the changes of default points in this sampled Chinese stock market.

5.2 Model validation

As there is no significant difference from the three default points in KMV model and the variance of all samples calculated with DD2: Current liabilities+ Long-term liabilities is bigger than the others, the following analysis in KMV model is based on the default point at DD2.

5.2.1 Statistical tests

The selected 32 listed companies can be separated into two groups, group 1 with 16 ST&*ST companies and group 2 with 16 blue chip companies. The ST&*ST companies are assumed to have higher credit risks than the blue chips companies since they suffer from bad financial statues. When applying the KMV model and Market Based (MB) model into the collection of Chinese listed companies, four sets

of default distance series, KMV-BLUE, KMV-ST, MB-BLUE, MB-ST, can be obtained and Table 3 shows the summary statistic description of the four variables and Table 4 shows the statistic tests among four variables from Gretl.

Table 3 Summary statistic description for default distance series from two models

	KMV model		Market based model	
	Bluechip	ST&*ST	Bluechip	ST&*ST
Mean	1.0954	0.88523	2.7988	2.6115
variance	1.22376	0.84851	1.34272	0.584606
Median	1.3041	1.0838	2.8173	2.7454
Kurtosis	0.55306	-0.4386	0.13377	0.59528
Skewness	-0.15289	-0.10194	-0.34639	-0.56811
Maximum	3.8839	3.043	5.5233	4.4594
Minimum	-2.9116	-2.0116	0.17165	0.46738

Table 4 Statistic tests among default distance series from two models

	F-test		T-test		W-test	
	F	P-value	T	P-value	Z	P-value
KMV-BLUE, KMV-ST	1.44224	0.07589*	-1.43054	0.1526	-1.49091	0.067992*
MB-BLUE, MB-ST	2.29679	6.73E-05***	-1.32188	0.1862	-1.48052	0.069367*
KMV-BLUE,MB-BLUE	1.09721	0.6521	-10.4182	2.05E-25***	-8.826	0.069367*
KMV-ST,MB-ST	1.45142	0.07098*	-14.1291	2.51E-45***	-10.1948	1.05E-24***

Note: All P-values is two tailed.

Null hypothesis (F-test): Difference of variance equals to zero.

Null hypothesis (T-test): Difference of means equals to zero.

Null hypothesis (Wilcoxon-test): Two medians are equal.

***Significantly different at 1% significant level.

**Significantly different at 5% significance level.

*Significantly different at 10% significant level.

5.2.2 Credit risk distinguishing capacity

Both the means in Bluechip group from two models are bigger than those in ST&*ST group. Both the two groups show significant difference in variance as F-tests illustrate and groups in market based model have higher variance. Although there is no significance difference in t-test between the Bluechip group and the ST&*ST group, none of the four series show normal distribution according to their values of kurtosis and skewnwss. Non parametric Wilcoxon tests are applied. And from the P-value at two tails in Wilcoxon tests, both two groups from same model have significant difference in median at 1% confidence level. Thus, the sample values of distance to defaults for Bluechip companies and ST&*ST companies are different. Further statics tests prove the assumption that ST&*ST companies have worse credit risk situation with lower value of distance to default. Both the two models are able to capture and

distinguish the credit risk from safe companies as BlueChips and worse companies as ST&*ST.

However, it is interesting to note the minimum value of default distance series in KMV model, which shows the impractical negative values. In Merton's model, the distance could be negative when equity value is lower than the default point. But in reality, the distance value turns to be zero once the default occurs. Both the two minimum negative values belong to heavily leveraged property industry. Besides, for Bluechip companies, the minimum values of default distance from two models are below those for ST&*ST companies, which indicates some possible misclassification of bankrupt companies as safe companies by the two models. Therefore, a further analysis about the impact of leverage ratio on the value of default distance is expected.

5.3 Further discussion on the differences between the two models

5.3.1 Regression analysis in the KMV model

Like any European type option pricing model, the key parameters of Merton's KMV model are company's asset value, face value of debt and volatility. Bystrom (2006) develops a simple spread model from Merton's options theory, which only contains two parameters (the leverage ratio and equity volatility), and find two models produce similar distance-to-default measures. In order to concentrate the key determinants in KMV model, the following analysis usesBystrom (2006) 'spread sheet' version of the KMV model and focus on the leverage ratio and equity volatility to estimate the distance to default in KMV model.

A simple linear regression model relating the changes of leverage ratio and equity volatility to the value of distance to default is reported in Table 5. As Bystrom (2006) documents, highly leveraged firms have the value of distance to default less sensitive to leverage changes than those of the average firm. This study separates the total sampled companies' default distance value from 2006 to 2011 into two groups, according to their leverage ratio. One group with 32 observations, the high leveraged companies, collects those companies whose leverage ratio is equal or above one, and other with 160 observations, the common leveraged companies, consists of the rest whose leverage ratio is below one. The leverage ratio is calculated as total liability/market value of equity.

Table 5 Cross-section regression in KMV model

DD=α+ β Leverage Ratio+ γ Equity Volatility+ ε								
	common leveraged companies				high leveraged companies			
	Coefficient	Std. E	t-ratio	p-value	Coefficient	Std. E	t-ratio	p-value
α	0.890365	0.120069	7.4154	<0.00001***	2.36741	0.523424	4.5229	0.0001***
β	1.15326	0.33121	3.482	0.00064***	0.000727	0.181489	0.004	0.99683
γ	-0.10791	0.022418	-4.8134	<0.00001***	-0.15793	0.049488	-3.1912	0.00339***
	R^2	0.133515	Adj.R^2	0.122477	R^2	0.265889	Adj. R^2	0.215261
	F(2, 157)	12.09592	P-value(F)	0.000013***	F(2, 29)	5.251784	P-value(F)	0.011312**

Note: ***Significantly different at 1% significant level.
**Significantly different at 5% significant level.

The regression results in common leveraged group shows that all regressions and estimated coefficients are statistically significant accounting to F and t statistic. Both the leverage ratio and equity volatility explain good percentage of the variability of distance to default estimated by the model. However, in the high leveraged group, the explanatory power of leverage ratio goes worse as there is no statistically significant in t statistic. The absolute coefficient of equity volatility increases with same significant level, which implies a stronger influence of equity volatility on the changes of value of default distance. Combined with the fundamental feature of Merton model, equity volatility becomes a critical parameter when the company is under a heavily leveraged ratio. The change of equity volatility is much more sensitive to the value of default distance in KMV model, especially when the company is out of money or technical bankrupt. In other words, KMV model, which rely largely on the equity volatility and leverage ratio, has better recognition ability to credit risk in common leveraged firms.

5.3.2 Regression analysis in the market based model

The second market based model contains only one parameter, the equity volatility, to predict the plausible default probability and early warning signal. Several empirical researchers, such as Curry, Elmer and Fissel(2001) and Campbell and Taksler (2002), have found the strong correlation between the volatility increases and credit deterioration. However, the calculation to capture this volatility in market based model is different from that in KMV model.

The total firm volatility should include both idiosyncratic volatility and systematic or market wide volatility. In KMV model, the calculation of equity volatility only captures the idiosyncratic part while in the market based model, the equity volatility is obtained under the asset pricing in a conditional CAPM framework. It involves both the two parts volatility and thus indicates a more accurate approach of estimating equity volatility. One thing should be noted is that idiosyncratic volatility can move very different from the market wide volatility. As in sampled companies, the annual average equity volatility in KMV model is 3.7233 while the value in market based

model is only 0.54037, which means much weaker market volatility during the data window. And this could also be one of the reasons much higher value in default distance from market based model. More statically inference between the equity volatility from two models will be examined in the following cross-section regression.

As shown in regression analysis in KMV model, equity volatility is particularly important for firms with a high leverage ratio when measuring the credit risk. It makes sense since investors may regard a company with almost no debt as unlikely to default even the companies' equity is highly volatile. In order to provide more statically significant inference about the relationship between default distance purely based on equity volatility and leverage ratio, a simple linear regression is followed and its results are shown in Table 6.

Table 6 Cross-section regression in Market Based model

DD=α+ β Leverage Ratio+ γ Equity Volatility+ ε								
	common leveraged companies				high leveraged companies			
	Coefficient	Std. E	t-ratio	p-value	Coefficient	Std. E	t-ratio	p-value
α	3.1709	0.259564	12.2163	<0.00001***	3.81481	0.649615	5.8724	<0.00001***
β	-0.234441	0.290836	-0.8061	0.42141	-0.312841	0.17075	-1.8322	0.07722*
γ	-0.684869	0.432801	-1.5824	0.11557	-0.969114	1.04291	-0.9292	0.36044
	R^2	0.021057	Adj.R^2	0.008587	R^2	0.156221	Adj.R^2	0.098029
	F(2, 157)	1.688543	P-value(F)	0.188127	F(2, 29)	2.684592	P-value(F)	0.085176*

Note: ***Significantly different at 1% significant level.
*Significantly different at 10% significant level.

The regression results show that in high leveraged group, the leverage ratio increases the explanatory power of regressor and more importantly its coefficient becomes statistically significant. The model R-square improves as well in the high leveraged group. These results support the theoretical robustness of the market based model and once again imply the particular effect of equity volatility on the measure of default risk in high leveraged companies. What is more, it fills the drawback in KMV model where leverage ratio doesn't show statistically significant impact on value of distance to default in high leveraged companies, which indicates the better explanatory power of market based model in heavily leveraged group.

However, the second market based model captures more market wide volatility and systematic risk as the variable of equity volatility from idiosyncratic stock price doesn't show any statically significance on the default measure combined market with individual effect. This differs from KMV model and implies that the default risk could be one systemic risk largely influenced by the macroeconomic situation.

6. Conclusion

This study applies two credit risk models to a sample of 32 Chinese listed non-financial companies including 16 Bluechip companies and 16 ST&*ST companies from 2006 to 2011 for expected default measurement. One is the basic option pricing model, the KMV model, and the other relies on the conditional version of capital asset pricing model, the market based model.

First, three different default points are set in the KMV model to test the sensitivity of default probability in Chinese listed companies. The credit risk doesn't change much with different default points, which is in contrast to the result of KMV Company that the prediction accuracy of KMV model is sensitive to the changes of default points. However, Chen, Wang, Wu (2010) draw the same conclusion that the predictive accuracy of the adjusted KMV model is stable to the changes of default points in Chinese small and medium enterprises (SMEs). This study examines the current liability structure and finds that both the Blue Chip and ST&*ST companies in Chinese stock market prefer to use short-term debt and thus results in the little difference among three default points.

Second, this study initially introduces the market based model and compares it with the KMV model in terms of the default measures. Both KMV model and the market based model are valid to distinguish risky firms and profitable firms. The values of distance to default in ST&*ST companies are lower than those in Bluechip companies, which is consistent with the assumption that ST&*ST company is more likely to default than the blue chips. However, the negative values of distance to default from the KMV model among highly leveraged firms give rise to the further discussion on the impact of leverage ratio to the changes of default measures.

Bystrȍm (2006) concludes that the key determinants in the KMV model are leverage ratio and equity volatility and, this study further examines the interaction effect of those two variables in both the KMV model and the market based model with cross-sectional regression. Similar to Bystrȍm (2006), it shows that highly leveraged firms have distances to default that are less sensitive to leverage changes than those of the average firm in the KMV model. When the company is under a heavily leveraged ratio, equity volatility becomes a critical parameter. However, in the market based model, the change of the leverage ratio becomes sensitive to the value of default distance in highly leveraged firms than those with average leverage. Different from the equity volatility in KMV, the calculation of the firm’s volatility in market based model captures both idiosyncratic and market wide volatility.

Thus, this study suggests that more effective default measure to highly leveraged firms is calculated by the market based model. This measure can also be calculated to improve the predictive default value from KMV model, in particular to firms whose capital structure is uncertainty or where accounting data is questionable. A further

extension of this research would be to examine whether the observed misclassification of safe and risky companies is due to the limitations of the two models or special company management. Besides, the insignificant statistical inference between idiosyncratic equity volatility in KMV model and volatility obtained under the conditional CAPM framework indicates the possible correlations of default probability with systemic macro-financial situation, which should also be an interesting topic for further study.

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Appendix I: List of sample companies

BlueChip Companies		
Code	Name	Industry
600663	Shanghai Lujiazui Finance&Trade Zone Development Co.,Ltd	utilities
900948	Inner Mongolia Yitai Coal Company Limited	utilities
600123	Shanxi Lanhua Sci-Tech Venture Co.,Ltd.	utilities
000042	Shenzhen Changcheng Investment Holding Co.,Ltd	properties
000024	China Merchants Property Development Co.,Ltd.	properties
600376	Beijing Capital Development Co.,Ltd.	properties
600216	Zhejiang Medicine Co.,Ltd.	conglomerates
600970	Sinoma International Engineering Co.,Ltd.	conglomerates
000623	Jilin Aodong Pharmaceutical Group Co., Ltd.	conglomerates
600519	Kweichow Moutai Co.,Ltd.	industrials
600150	China CSSC Holdings Limited	industrials
600869	Yantai Changyu Pioneer Wine Company Limited	industrials
600739	Liaoning Chengda Co.,Ltd.	commerce
600785	Yinchuan Xinhua Commercial（Group）Co.,Ltd.	commerce
600729	Chongqing Department Store Co.,Ltd.	commerce
600859	Beijing Wangfujing Department Store (Group) Co.,Ltd.	commerce

ST&*ST Companies		
Code	Name	Industry
000504	Beijing CCID Media Investments Co.,Ltd.	utilities
600087	Nanjing Tanker Corporation	utilities
600751	Tianjin Marine Shipping Co.,Ltd.	utilities
000505	Hainan Pearl River Holdings Co.,Ltd.	properties
600766	Yantai Yuancheng Enterprise Group Co.,Ltd.	properties
000545	Jilin Pharmaceutical Co., Ltd.	properties
000576	Jiangmen Sugarcane Chemical Factory (Group) Co.,Ltd.	conglomerates
000660	South China Holdings Limited	conglomerates
600359	Xinjiang Talimu Agriculture Development Co.,Ltd.	conglomerates
000669	Jilin Leading Technology Development Co.,Ltd.	industrials
600084	Citic Guoan Wine CO.,LTD	industrials
600515	Hainan Island Construction Co., Ltd	industrials
000409	Taifu Industry Co., Ltd.	commerce
000420	Jilin Chemical Fibre Co.,Ltd.	commerce
000509	Huasu Holdings Co.,Ltd	commerce
000595	Xibei Bearing Co.,Ltd.	commerce

Appendix II: Default measure from KMV model and market based (MB) model

Stock	Year	DD0	DD1	DD2	MV
600515	2006	0.002879	0.003358	0.0024	2.356059
	2007	0.083346	0.087539	0.079152	1.051764
	2008	-0.01006	0.005561	-0.02568	2.185291
	2009	1.419866	1.474901	1.364832	2.45046
	2010	1.45724	1.459758	1.454722	2.382222
	2011	1.064483	1.505757	0.623209	3.064251
000504	2006	1.943783	1.944726	1.94284	2.883144
	2007	1.26376	1.264107	1.263414	2.269737
	2008	0.082024	0.082113	0.081934	2.359272
	2009	1.444124	1.444561	1.443686	2.644713
	2010	2.227656	2.228279	2.227033	2.703447
	2011	2.526144	2.527095	2.525193	2.813061
600087	2006	1.740768	2.171545	1.309991	2.941944
	2007	1.087736	1.344866	0.830606	2.951932
	2008	0.032679	0.071119	-0.00576	2.913013
	2009	0.04707	0.076278	0.017862	2.960251
	2010	0.013072	0.066299	-0.04015	2.975913
	2011	-0.01334	0.053929	-0.08061	2.954146
600751	2006	0.933984	0.933984	0.933984	3.028976
	2007	1.504952	1.515069	1.494835	2.344577
	2008	0.01909	0.020968	0.017212	2.402294
	2009	1.420362	1.420362	1.420362	2.761983
	2010	2.03622	2.192537	1.879904	3.058736
	2011	1.733735	1.742794	1.724675	3.061892
000505	2006	0.058087	0.067182	0.048992	2.30776
	2007	1.172652	1.18605	1.159254	1.10324
	2008	0.04542	0.051558	0.039282	0.6487
	2009	0.054058	0.056367	0.051749	2.485518
	2010	1.661386	1.867835	1.454937	2.986967
	2011	1.292888	1.367742	1.218035	3.479864
600766	2006	0.022155	0.025166	0.019145	3.142648
	2007	1.074444	1.085772	1.063117	1.698764
	2008	0.009855	0.009866	0.009845	1.972522
	2009	0.06472	0.067378	0.062062	3.27186
	2010	1.679484	1.679484	1.679484	4.20551
	2011	1.687763	1.687763	1.687763	3.516605

Note:

DD: distance to default measure from KMV

DD0: current liabilities+0.5×long-term liabilities,

DD1: current liabilities, DD2: current liabilities+long-term liabilities.

MB: distance to default measure from market based model

(Continued)

Stock	Year	DD0	DD1	DD2	MV
000545	2006	0.013229	0.015792	0.010666	1.239388
	2007	1.255123	1.261317	1.248929	0.788906
	2008	0.083798	0.084376	0.083219	0.467384
	2009	1.688732	1.693075	1.684389	2.829173
	2010	1.843294	1.843294	1.843294	3.174706
	2011	1.873552	1.873552	1.873552	1.127842
000576	2006	0.044607	0.047219	0.041996	1.942784
	2007	1.192566	1.225233	1.1599	1.853736
	2008	0.038984	0.039818	0.038151	1.819427
	2009	1.747322	1.818456	1.676187	1.644778
	2010	2.144826	2.153797	2.135855	2.593422
	2011	1.731362	1.747531	1.715194	1.52473
000660	2006	-0.31564	-0.30811	-0.32317	2.264228
	2007	-0.07669	-0.07391	-0.07946	2.595876
	2008	-0.39892	-0.38771	-0.41013	2.729698
	2009	-0.09533	-0.0937	-0.09696	2.788912
	2010	-0.04316	-0.03404	-0.05227	3.465573
	2011	-1.8333	-1.65504	-2.01156	3.376456
600359	2006	0.022051	0.023153	0.020949	2.407826
	2007	0.722519	0.744425	0.700612	2.416601
	2008	0.028385	0.033702	0.023069	2.433278
	2009	1.225319	1.295825	1.154812	2.420459
	2010	0.995898	1.085449	0.906347	2.570829
	2011	-0.03623	0.189319	-0.26178	3.393784
000409	2006	1.729212	1.729453	1.728971	2.513919
	2007	1.613774	1.613823	1.613726	2.107094
	2008	1.422454	1.422608	1.4223	0.819427
	2009	2.062832	2.062901	2.062762	2.148467
	2010	3.04306	3.043164	3.042955	4.07228
	2011	2.877561	2.877688	2.877433	4.459397
000420	2006	0.008982	0.032798	-0.01483	2.905284
	2007	1.038072	1.107909	0.968235	3.074939
	2008	-0.04168	-0.02859	-0.05476	3.104776
	2009	0.020247	0.024773	0.015721	3.398478
	2010	0.725817	0.87437	0.577264	3.692778
	2011	-0.36173	-0.177	-0.54645	3.72926

(Continued)

Stock	Year	DD0	DD1	DD2	MV
000509	2006	-0.04464	-0.04463	-0.04464	2.705408
	2007	1.299069	1.29908	1.299059	2.822051
	2008	0.010488	0.01049	0.010486	2.927643
	2009	1.650938	1.650949	1.650927	3.033952
	2010	1.704517	1.704524	1.70451	3.16855
	2011	2.059481	2.059481	2.059481	3.293499
000595	2006	0.029058	0.029617	0.028499	2.727548
	2007	1.105574	1.106657	1.104492	2.953035
	2008	0.077556	0.077646	0.077466	3.162495
	2009	1.676895	1.678388	1.675401	3.350864
	2010	1.769221	1.770749	1.767692	3.515086
	2011	1.314532	1.316917	1.312147	3.654221
000669	2006	1.3929	1.476805	1.308995	2.523449
	2007	1.283244	1.306569	1.259919	2.35121
	2008	0.1008	0.100815	0.100785	2.208535
	2009	1.731596	1.731701	1.731492	2.128268
	2010	1.78748	1.78751	1.787451	2.050019
	2011	1.945584	1.945632	1.945536	1.992314
600084	2006	-0.02922	-0.02345	-0.035	2.615388
	2007	0.88249	0.976357	0.788624	2.912108
	2008	-0.11755	-0.09314	-0.14196	2.88235
	2009	1.753888	1.843294	1.664483	2.876243
	2010	2.122501	2.205553	2.03945	3.301081
	2011	2.282209	2.431787	2.13263	3.734152
900948	2006	2.24838	2.252816	2.252816	2.976115
	2007	1.867689	1.868895	1.868895	1.781282
	2008	1.517271	1.517271	1.517271	0.719933
	2009	1.274775	1.274775	1.274775	0.224697
	2010	2.049532	2.082661	2.082661	2.695112
	2011	2.765545	2.823289	2.823289	3.131598
600123	2006	1.588212	1.729378	1.447045	2.982707
	2007	1.400386	1.467443	1.33333	2.914805
	2008	0.041258	0.051877	0.03064	2.896492
	2009	1.411106	1.459781	1.362431	3.058483
	2010	1.697967	1.762408	1.633526	3.110135
	2011	1.983307	2.028391	1.938223	3.021926

(Continued)

Stock	Year	DD0	DD1	DD2	MV
000042	2006	0.056334	0.056334	0.017656	2.786906
	2007	0.930126	0.930126	0.634805	2.817338
	2008	-0.06755	-0.06755	-0.17608	2.817307
	2009	0.053698	0.053698	0.020181	2.817158
	2010	0.030857	0.030857	-0.00586	2.817443
	2011	0.660762	0.660762	-0.44385	2.817564
000024	2006	0.004381	0.028382	-0.01962	3.095192
	2007	1.026627	1.081626	0.971628	2.60348
	2008	-0.01328	0.007683	-0.03424	2.233195
	2009	0.038513	0.044162	0.032863	2.274724
	2010	-0.02046	-0.00338	-0.03754	2.920016
	2011	-2.06128	-1.21097	-2.91159	2.703094
600376	2006	-0.10702	-0.1006	-0.11343	3.275804
	2007	-0.08726	-0.06483	-0.10969	2.545445
	2008	-0.18557	-0.13957	-0.23157	2.181725
	2009	0.027199	0.043976	0.010421	3.110861
	2010	-0.03368	-0.00533	-0.06202	3.524482
	2011	-0.2238	-0.16782	-0.27977	5.523282
600663	2006	1.457558	1.460837	1.454279	2.074685
	2007	1.431711	1.431944	1.431478	0.822703
	2008	0.0531	0.053138	0.053061	1.840759
	2009	1.666704	1.673968	1.659441	2.038216
	2010	1.59222	1.66712	1.517321	2.333945
	2011	0.629956	0.713751	0.546161	2.305942
600216	2006	0.015091	0.018762	0.01142	3.806124
	2007	1.043341	1.061246	1.025437	4.023236
	2008	0.078115	0.078733	0.077496	4.021615
	2009	2.075068	2.084488	2.065648	4.022801
	2010	2.410474	2.412616	2.408332	4.023904
	2011	2.884747	2.886248	2.883245	4.02403
600970	2006	-0.05153	-0.05124	-0.05181	3.064628
	2007	0.143146	0.145325	0.140967	2.718581
	2008	-0.18497	-0.18284	-0.1871	2.594179
	2009	0.00737	0.00836	0.00638	3.64716
	2010	0.045122	0.045541	0.044703	3.8012
	2011	0.434715	0.45993	0.409501	4.174516

(Continued)

Stock	Year	DD0	DD1	DD2	MV
000623	2006	1.534704	1.546301	1.523107	1.845108
	2007	0.976773	0.977125	0.97642	3.025253
	2008	1.262512	1.263741	1.261284	2.770291
	2009	1.898022	1.898701	1.897344	2.567042
	2010	2.009855	2.010794	2.008915	2.54653
	2011	2.40679	2.408424	2.405155	2.99814
600519	2006	0.088313	0.088313	0.088313	0.790336
	2007	2.104638	2.104638	2.104638	1.770838
	2008	2.166309	2.166309	2.166309	2.116732
	2009	2.992644	2.992742	2.992547	2.229984
	2010	3.130033	3.130128	3.129938	2.403819
	2011	3.586734	3.586884	3.586583	2.619896
600150	2006	1.421554	1.464016	1.379093	0.800238
	2007	1.359428	1.372498	1.346358	3.345671
	2008	-0.0118	-0.00483	-0.01876	2.982999
	2009	0.047449	0.052052	0.042847	4.202131
	2010	1.075527	1.273181	0.877873	4.085497
	2011	0.45196	0.680817	0.223103	4.448214
600869	2006	1.561342	1.561342	1.561342	4.024651
	2007	1.860147	1.860147	1.860147	4.817361
	2008	1.953063	1.953063	1.953063	4.560637
	2009	2.668941	2.669579	2.668302	4.942008
	2010	2.652367	2.652367	2.652367	4.793835
	2011	3.883886	3.883886	3.883886	5.027943
600739	2006	0.072205	0.072261	0.072148	0.391076
	2007	1.004987	1.005048	1.004927	0.181283
	2008	0.08951	0.089535	0.089486	0.171653
	2009	1.741398	1.744174	1.738622	0.282439
	2010	1.907936	1.926349	1.889524	0.39978
	2011	1.517358	1.544108	1.490608	0.375226
600785	2006	0.035121	0.036759	0.033484	1.495022
	2007	1.423233	1.423233	1.423233	2.394482
	2008	0.06264	0.06264	0.06264	2.356867
	2009	1.644172	1.644172	1.644172	2.494383
	2010	1.8628	1.8628	1.8628	2.469085
	2011	2.362452	2.362452	2.362452	2.470469

(Continued)

Stock	Year	DD0	DD1	DD2	MV
600729	2006	1.329628	1.390236	1.269021	2.462162
	2007	1.267306	1.284324	1.250288	2.816228
	2008	0.052192	0.053018	0.051367	1.344552
	2009	1.618951	1.618951	1.618951	2.791959
	2010	1.333965	1.333965	1.333965	3.398327
	2011	1.716903	1.716903	1.716903	3.421281
600859	2006	1.268801	1.268801	1.268801	3.163309
	2007	1.483922	1.483922	1.483922	2.803177
	2008	0.047196	0.047196	0.047196	2.953086
	2009	1.807997	1.865158	1.750836	4.044952
	2010	2.305782	2.305782	2.305782	4.129312
	2011	2.494934	2.494934	2.494934	4.030453

Appendix III: Mat lab code – asset value, asset volatility, and DD calculation

```
clc
clear all

SigE=xlsread('D:\KMV\DATA.xls','sheet1',’A2:A183’);
rf= xlsread('D:\KMV\DATA.xls','sheet1',’B2:B183’);
VE= xlsread('D:\KMV\DATA.xls','sheet1',’C2:C183’);
D= xlsread('D:\KMV\DATA.xls','sheet1',’D2:D183’);
DP= xlsread('D:\KMV\DATA.xls','sheet1',’E2:E183’);

n=length(VE);
for i=1:n
c1=D(i)
c2=VE(i)
c3=SigE(i)
c4=DP(i)
R=rf(i)
a=fsolve(@(x)myfun(x,c1,c2,c3,R),[c2;c3],optimset('Display','iter'))
VA(i)=a(1,1);
SigA(i)=a(2,1);
DD(i)=(VA(i)-c4)/(VA(i)*SigA(i))
EDF(i)=1-normcdf(DD(i),0,1)
end
```

M-File:

```
function G = myfun( x,c1,c2,c3,R )
d1=(log(x(1)/c1)+(R+(x(2)^2)/2))/x(2);
G=[x(1)*normcdf(d1,0,1)-exp(-R)*c1*normcdf(d1-x(2),0,1)-c2;normcdf(d1,0,1)*x(1)
*x(2)/c2-c3];
```

Appendix IV: Eviews code - BV-GARCH-M model

```
' change path to program path
cd %path
' load workfile
load intl_fin.wf1
' dependent variables of both series must be
continues
smpl @all
series y1 = dlog(excessstockreturn)
series y2 = dlog(excessmarketreturn)

' set sample
' first observation of s1 need to be one or
two periods after
' the first observation of s0
sample s0 1/1/2006 31/12/2011
sample s1 1/2/2006 31/12/2011

' initialization of parameters and starting
values
' change below only to change the
specification of model
smpl s0

'get starting values from univariate GARCH
'equation eq1.arch(m=100,c=1e-5) y1 c
'equation eq2.arch(m=100,c=1e-5) y2 c

equation
eq1.arch(archm=var,m=100,c=1e-5) y1 c
equation
eq2.arch(archm=var,m=100,c=1e-5) y2 c

'save the conditional variances
eq1.makegarch garch1
eq2.makegarch garch2



' declare coef vectors to use in bi-variate
GARCH model
' see above for details
%path = @runpath
'coef(3) omega
' omega(1)=(eq1.c(2))^.5
' omega(2)=0
' omega(3)=eq2.c(2)^.5

'coef(2) alpha
' alpha(1) = (eq1.c(3))^.5
' alpha(2) = (eq2.c(3))^.5

'coef(2) beta
' beta(1)= (eq1.c(4))^.5
' beta(2)= (eq2.c(4))^.5

'new values
        ' declare coef vectors to use in
        GARCH
model
coef(2) lambda
        lambda(1) = eq1.c(1)
  lambda(2) = eq2.c(1)

coef(2) mu
      mu(1) = eq1.c(2)
      mu(2)= eq2.c(2)

coef(3) omega
      omega(1)=(eq1.c(3))^.5
      omega(2)=0
      omega(3)=eq2.c(3)^.5

coef(2) alpha
alpha(1) = (eq1.c(4))^.5
      alpha(2) = (eq2.c(4))^.5

coef(2) beta
      beta(1)= (eq1.c(5))^.5
      beta(2)= (eq2.c(5))^.5
' constant adjustment for log likelihood
!mlog2pi = 2*log(2*@acos(-1))
```

```
'coef(2) mu
' mu(1) = eq1.c(1)
' mu(2)= eq2.c(1)


'series cov_y1y2 = @cov(y1-mu(1),
y2-mu(2))
'series var_y1 = @var(y1)
'series var_y2 = @var(y2)

'series sqres1 = (y1-mu(1))^2
'series sqres2 = (y2-mu(2))^2
'series res1res2 = (y1-mu(1))*(y2-mu(2))

series cov_y1y2 =
@cov(y1-mu(1)-lambda(1)*garch1,
y2-mu(2)-lambda(2)*garch2)

series var_y1 =
@var(y1-lambda(1)*garch1)
series var_y2 =
@var(y2-lambda(2)*garch2)

series sqres1 =
(y1-mu(1)-lambda(1)*garch1)^2
series sqres2 =
(y2-mu(2)-lambda(2)*garch2)^2

series res1res2 =
(y1-mu(1)-lambda(1)*garch1)*(y2-mu(2)-la
mbda(2)*garch2)

loglbvgarch
'old values
'bvgarch.append @logllogl
'bvgarch.append sqres1 = (y1-mu(1))^2
'bvgarch.append sqres2 = (y2-mu(2))^2
'bvgarch.append res1res2 =
(y1-mu(1))*(y2-mu(2))

' squared errors and cross errors
bvgarch.append @logllogl
bvgarch.append sqres1 =
(y1-mu(1)-lambda(1)*garch1)^2
bvgarch.append sqres2 =
(y2-mu(2)-lambda(2)*garch2)^2
```

```
'old values
' use var-cov of sample in "s1" as
starting value of variance-covariance
matrix

bvgarch.append res1res2 =
(y1-mu(1)-lambda(1)*garch1)*(y2-mu
(2)-lambda(2)*garch2)

' calculate the variance and covariance
series
bvgarch.append var_y1    =
omega(1)^2 + beta(1)^2*var_y1(-1) +
alpha(1)^2*sqres1(-1)
bvgarch.append var_y2    =
omega(3)^2+omega(2)^2 +
beta(2)^2*var_y2(-1) +
alpha(2)^2*sqres2(-1)
bvgarch.append cov_y1y2 =
omega(1)*omega(2) +
beta(2)*beta(1)*cov_y1y2(-1) +
alpha(2)*alpha(1)*res1res2(-1)

' determinant of the
variance-covariance matrix
bvgarch.appenddeth = var_y1*var_y2 -
cov_y1y2^2

' inverse elements of the
variance-covariance matrix
bvgarch.append invh1 = var_y2/deth
bvgarch.append invh3 = var_y1/deth
bvgarch.append invh2 =
-cov_y1y2/deth

' log-likelihood series
bvgarch.appendlogl =-0.5*(!mlog2pi +
(invh1*sqres1+2*invh2*res1res2+invh
3*sqres2) + log(deth))

' remove some of the intermediary
series
' bvgarch.append @temp invh1 invh2
invh3 sqres1 sqres2 res1res2 deth
' estimate the model
smpl s1
bvgarch.ml(showopts, m=100, c=1e-5)
```

Appendix V: Regression Analysis on KMV model and Market based model

Model 1: OLS, using observations 1-32
Distance to default in KMV among high leveraged group
Dependent variable: DD2

	Coefficient	Std. Error	t-ratio	p-value	
const	2.36741	0.523424	4.5229	0.00010	***
Leverage Ratio	0.000726804	0.181489	0.0040	0.99683	
Equity volatility	-0.157927	0.049488	-3.1912	0.00339	***

Mean dependent var	1.037154	S.D. dependent var	1.086190
Sum squared resid	26.84942	S.E. of regression	0.962207
R-squared	0.265889	Adjusted R-squared	0.215261
F(2, 29)	5.251784	P-value(F)	0.011312
Log-likelihood	-42.59817	Akaike criterion	91.19633
Schwarz criterion	95.59354	Hannan-Quinn	92.65388

Model 2: OLS, using observations 1-160
Distance to default in KMV among common leveraged group
Dependent variable: DD2

	Coefficient	Std. Error	t-ratio	p-value	
const	0.890365	0.120069	7.4154	<0.00001	***
Leverage Ratio	1.15326	0.33121	3.4820	0.00064	***
Equity volatility	-0.10791	0.0224184	-4.8134	<0.00001	***

Mean dependent var	0.980955	S.D. dependent var	1.010409
Sum squared resid	140.6541	S.E. of regression	0.946512
R-squared	0.133515	Adjusted R-squared	0.122477
F(2, 157)	12.09592	P-value(F)	0.000013
Log-likelihood	-216.7205	Akaike criterion	439.4411
Schwarz criterion	448.6666	Hannan-Quinn	443.1872

Model 3: OLS, using observations 1-32
Distance to default in Market Based Model among high leveraged group
Dependent variable: MB

	Coefficient	Std. Error	t-ratio	p-value	
const	3.81481	0.649615	5.8724	<0.00001	***
Leverage ratio	-0.312841	0.17075	-1.8322	0.07722	*
Equity volatility	-0.969114	1.04291	-0.9292	0.36044	

Mean dependent var	2.632779	S.D. dependent var	0.939058
Sum squared resid	23.06614	S.E. of regression	0.891843
R-squared	0.156221	Adjusted R-squared	0.098029
F(2, 29)	2.684592	P-value(F)	0.085176
Log-likelihood	-40.16811	Akaike criterion	86.33622
Schwarz criterion	90.73343	Hannan-Quinn	87.79377

Model 4: OLS, using observations 1-160
Distance to default in Market Based Model among common leveraged group
Dependent variable: MB

	Coefficient	Std. Error	t-ratio	p-value	
const	3.1709	0.259564	12.2163	<0.00001	***
Leverage ratio	-0.234441	0.290836	-0.8061	0.42141	
Equity volatility	-0.684869	0.432801	-1.5824	0.11557	

Mean dependent var	2.719673	S.D. dependent var	0.994455
Sum squared resid	153.9304	S.E. of regression	0.990176
R-squared	0.021057	Adjusted R-squared	0.008587
F(2, 157)	1.688543	P-value(F)	0.188127
Log-likelihood	-223.9363	Akaike criterion	453.8726
Schwarz criterion	463.0981	Hannan-Quinn	457.6188