# Financial Distress Prediction Models for Credit Unions in Taiwan

## Abstract

We are going to examine the determinants and prediction model of the financial distress on non-profit organization (NPO；Credit Unions) during 2001-2009. Tested via Merton distance to default (DD), Logit, and hazard model, researchers discovered that the financial distress assessment indicator presented by Merton DD model did not show significant predictive capability; in addition, the financial distress assessment indicator of Merton DD model, which was constructed with z-score, possessed improved predictive capability, but reducing equity volatility could further improve the predictive capability. When it comes to out-of-sample predictive capability, the performances of single financial distress prediction indicator or Logit model were no better than combined hazard models and Merton DD.

The estimated performance of hazard functions has significant relationship to the risk of financial distress generated by credit unions; this includes the assets size, profitability, capital adequacy ratio, liquidity, the reserves capacity for loan ratio in financial risk, operating efficiency, labor cost ratio, share capital growth rate in management efficiency, and the spreads from deposit and loan in banking industry of the holistic exterior environment.

Different models are evolved with different properties of research data, producing wider practical utility range and smaller assumption limitation. To prevent Credit Unions from financial distress requires Hazard model combined with modified Merton DD model, which could timely reflect market volatility and predict when distress would occur.

Keywords: NPO, credit unions, financial distress, hazard model, Logit model, Merton DD model

## 1. Introduction

Financial Distress Prediction (FDP) has been widely discussed in the industry and academia that the importance of FDP became more salient especially when global financial distress occurred in 2007. It involves developing statistics models to forecast an omen of financial distress before a company actually going bankrupt. Accurate FDP model would be extremely valuable in the real world so as to prevent huge social capital triggered by shutdown of the companies, such as Enron and Lehman Brothers.

FDP model attempts to predict company bankruptcy based on publicly accessible information such as financial reports and some studies also include factors of economy and industry that widely influence bankruptcy prediction. Accurate FDP model would prevent banks, credit unions, investment banks, and other financial institutions from lending money to lenders that are likely to go bankrupt, and never repay the loans. Meanwhile, financial investment institutions could avoid investing in problematic companies to improve the risk return trade-off from investment. Enterprises could establish long-term cooperation with companies that are predicted as sturdy in the future to extend the survival and longevity. In addition, the model could provide information for government sectors to do early intervention; early intervention includes assisting problematic companies legitimately handling possible cause of problems, avoiding illegal activities such as issuing stocks and raising funds, or avoiding taxation and claiming dilution.

Accurate FDP model helps not only enterprises but also individuals and other units invest in sturdy companies to gain profits. In brief, accurate FDP model can increase individual investment confidence, and granting loans to sturdy companies to develop bilateral relationships will continuously benefit everyone in steady economic growth.

Prediction accuracy is the main factor to determine the accuracy of FDP model. To measure the prediction accuracy is to evaluate the application of a set of new data, to see if it shows a good prediction result of future default probability, and at the same time, it should take account of real world situation, which will adjust with different environments; the process also involves with subjective determination. The default prediction model is the main pattern of FDP model. The prediction does not guarantee definite occurrence, but the confidence level information that is used to predict default probability is of great value. The setting of interest rate premiums on loans depends on expected default probability of lenders; government sectors will pay attention to each activity in companies of high default probability; investors will calculate the fair market value of stocks based on enterprises¡ expected future cash flow weighted with survival rate (1- default probability); the fair market value can be used to compare with market prices, so as to determine whether to buy, sell or hold the stocks.

Currently, FDP model can be divided into historical data model and market data model. Historical data model adopts past financial and non-financial data in companies to evaluate credit risks; market data model is based on market information, such as daily stock prices or return rate of stock prices, to assess default probability. Normally the biggest difference of historical data and market data models lies in the data prevalence and availability. Historical data is past information, so it can not reflect instant real situation and flexible adjustment, and its financial report has window dressing effect in accounting; while market data has dynamic characteristics, so it can timely reflect the real situation of credit risks.

In the market data model, Merton (1974) firstly discussed the option right proposed by Black and Scholes (1973).

With the development and application by KMV corporation, it has been a widely utilized prediction model for research and experiment in academia; the model is Merton distance to default model (Merton DD model), which views the equity of the company as European call that regards company¡s asset as subject matter, and considers due debt as strike price. When the value of a company is higher than due debt, it is in-the-money, which means the shareholders in the company possess solvency; on the contrary, if the value of a company is lower than due debt, it is out-of-the-money, which means shareholders lack solvency so that they give up their right of management. When out-of-the-money happens, it indicates default, so the creditor can take over the company and pays its debt. This model considers the strike value and the volatility of a company hard to observe, so Merton retrieves the expected default probability via evaluating the occurrence rate of out-of-the-money situation; the so called default probability means the probability of creditor unable to pay its debt in time.

Here the research attempts to follow the three assumptions proposed by Bharath and Shumway (2008). First of all, we doubt that the Merton DD model has statistics significance in predicting the default probability ( π _merton), but constructed reduced-form model should be examined beforehand, in order to prove a better predictive capability than Merton DD model. Secondly, we doubt that the functional form of using Merton DD model to construct linear combination formula can effectively predict the occurrence of default, but likewise, linear combination constructed prediction model should be tested for statistics significance. Thirdly, we doubt that the functional form of Merton DD model helps predict the default probability, but we should examine the existence of statistics significance of the default probability without Merton DD model.

To test the three assumptions, we currently utilize the following methods. The first one is to bring Merton probability (π_merton) into the default data predicted by hazard model during 2001-2009, and compare the significance of π_merton and the probability of simplified linear combination (π_shumway). The second one is to compare the out-of-sample predictive capability of π_merton and π_shumway in different models. The third one is to measure the factors affecting the default risks by Logit model.

With substantive examination, we discover that part of the result has something in common with research in literature. The first assumption is negative, because π_merton lacks statistics significance in predicting probability, and if considering other default prediction variables to improve π_merton. We discover that certain situations support the second assumption that linear combination prediction model constructs with π_shumway can improve predictive capability. In hazard model, π_shumway has statistics significance, and it performed better on out-of-sample predictive capability, but by modifying π_shumway, the simplified linear combination probability value (π_β_down) has better significance. Finally, we discover that some situations are unable to support the third assumption. π_merton has low contribution degree, no matter in the reduced form model or the variable π_shumway constructed model. In conclusion, the probability value of modified π_merton has greater default predictive capability, but the functional form of Merton model is needless.

Goddard et al. (2008) researched on the determinants through liquidation or acquisition for U.S. credit unions during 2001-2006, indicating that the risk affecting credit unions to terminate operation shows an inverse relationship with asset scale and profitability, while they showed a direct relationship with asset liquidity. With limited growth, credit unions are less likely to be the targets of acquisition, but they are easier to have financial distress. Credits unions with low capitalization and small loans portfolios are easier to be the targets for acquisition.

Credit unions are non-profit financial cooperatives. Each credit union is governed by its members, and they elect non-salaried volunteer officers and directors from the membership. Each member has one vote, instead of depending on the amount of financial stake each member owns. In the end of 2009, there were 336 credit unions in Taiwan, around 200,000 membership, and total assets of about 23.5 billion NT dollars. The asset and membership of Taiwan credit unions has increased in this recent decade, but the number of credit unions has significantly decreased. As the scale of credit unions expands and the business gets more complicated, the original service pattern done by non-salaried volunteers now requires the involvement of salaried employees. Goddard et al. (2002) indicated that common bond is the foundation of the composition of membership in credit unions, and restriction of membership to the residents in the same community and the employees in the same company, or other groups and organizational affiliation, such as church groups.

Goddard et al. (2008) indicated that the diversity of product services would increase along with the growing number of members in large-scale credit unions. Tokle and Tokle(2000), Feinburg(2001), Feinburg and Rahman(2001), and Schmid(2005) all pointed out that many credit unions in the U.S. provide an array of retail financial services similar to those of banks and savings & loan institutions. In addition, they also offer services such as interest-bearing business checking accounts, commercial loans, agricultural loans, and venture capital loans, etc. Credit unions consistently provide investment service products like banker acceptances, cash forward agreements and reverse purchase transactions, etc. Previously mentioned product offerings make credit unions in the U.S. have no significant gaps between mainstream financial service industries.

Thus, we attempt to see whether Taiwan¡s NPO (credit unions) are different from those showed in the literature in choosing financial distress prediction model. Generally, companies have the evaluation from credit rating institutions, but NPOs do not have similar professional institution to evaluate them. Their financial operation is neither public nor transparent, so it is usually unable to reverse the situation when financial distress strikes. Examined via the models above, we can offer NPOs a set of common operation model to predict financial distress.

This paper will be structured as follows: the second part is literature review, the third part is theoretical development and methodology, the fourth party is data and model specification, the fifth part is empirical evidence & results, and the last part is conclusion.

## 2. Literature review

None of the countries in the world could escape from the economic tsunami happened years ago. After the storm struck, governments around the world successively promoted policies to rescue the financial market, trying to avoid a great number of enterprises going bankruptcy and leading the whole economy going into depression. The operation of banking business also faced a major trial, and thus, the prediction of default probability has become a focus for governments and investors, and the financial report and ratings of public information are crucial factors. Following is the process of development in financial distress prediction:

A. Beaver (1966, 1968a, b) is the most notable on the analysis of univariate. Then Altman (1968) firstly mentioned measuring leverage degrees of companies with Altman¡s ¡Z-score¡ that leverage degree is the ratio of market value of equity and book value of liabilities. It is a Multiple Discriminant Analysis (MDA), which was also further studied by Deakin (1972) and Edminster (1972). Ohlson (1980) utilized Logistic model to develop the prediction model of financial distress, using ¡O-score¡ to construct default prediction model, which became a logit and probit model, a qualitative-response model.

Later Jones (1987) and Hillegeist, Keating, Cram, and Lundstedt (2004) followed the same direction to propose a model of corporate default probability, discussing certain variables of companies and the degree of co-variances as time passed.

B. As for market-based model, Black and Scholes (1973), Merton (1974), Fisher, Heinkel, and Zechner (1989), and Leland (1994) indicated that the process of asset formation follows the rules of geometric Brownian motion. In previous model, distance to default was used to measure the conditional default probability of companies and calculated by the standard deviation of annual asset growth rate; it showed that the asset value of a company was greater than its liabilities.

Stein (2000), Sobehart and Stein (2000), and Sobehart and Keenan(1999, 2002a, 2002b) doubted that Merton DD models could effectively make predictions; Kealhofer and Kurbat (2001) even doubted that the Merton DD-like model developed by KMV corporation could show information such as traditional credit ratings and accounting statement.

Crosbie and Bohn (2002) and Kealhofer (2003) pointed out that Moody¡s KMV, first empirically conducted the prediction of default probability on listed companies by adopting the covariance relationship between market value of corporate equity and the information of liabilities. Duf e and Lando (2001) stated that distance of default may not be accurately measured, and the degree of default probability depends on the measurement of the distance of default, and it could also be influenced by other variables at the same time; the determinants that affect corporate conditional default probability are those that influence the financial sturdiness of companies, such as industry categories, the distribution of product categories, and overall environmental variables, etc., all of them would influence the profits and leverage degree of companies.

Duffie, Saita, and Wang (2007) indicated that Merton DD probability prediction model possesses significant predictive capability under a consecutive time series of default probability structure; Campbell, Hilscher, and Szilagyi (2007) pointed out that when the indicator $\pi$ considered other variables, which are related to bankruptcy in hazard models, its predictive capability on bankruptcy would become relatively weaker.

C. Default probability prediction model emphasizes on the analysis of duration. Lane, Looney, and Wansley(1986) firstly proposed time-independent covariates aiming at analyzing banks¡ default prediction model; they usually adopted Cox proportional-hazard model, because Survival Model(SM) was not as prevalent as mainstream models like MDA and Logit Model, and the prediction accuracy of SM was just about the same as out-of-sample forecasts done by MDA, while SM had lower Type I errors; when Crapp and Stevenson (1987) used Cox model to analyze part of Credit Unions in Australia, they discovered similar situations. Lee and Urrutia (1996) proposed that they used the duration model in the Weibull distribution of default time to do bankruptcy prediction of insurance companies, and at the same time, compared the difference between duration and logit models; they discovered that duration model was more capable of finding out significant variable than logit model. Other relevant duration analysis done by Shumway (2001), Chava and Jarrow (2004), and Hillegeist, Keating, Cram, and Lundstedt (2004), etc. were also used to predict bankruptcy.

Shumway (2001) used discrete duration model, which possessed time-dependent covariates. This is the first time in empirical examination to adjust standard errors to run multi-period logit model analysis. Likewise, he discovered that current survival model (SM) theory outperformed traditional mainstream MDA and Logit Model. Empirically, in out-of-sample forecasts, Shumway SM was obviously better than MDA and Logit Model, which were also considered Type I errors, and their errors were below 10%, also below the real world situation. In predicting one-year default, Hillegeist, Keating, Cram, and Lundstedt (2004) adopted the same method. When Hillegeist, Keating, Cram, and Lundstedt (2004) utilized Black¡Scholes¡Merton model to calculate and estimate theoretical default probability, they discovered that the distance of default was insufficient to explain the variation of corporate default probability. Bharath and Shumway(2004) and Campbell, Hilscher, and Szilagyi (2005) also discovered that when taking the corporate leverage degree in the market and variances into account, the distance of default could not offer sufficient default information. Bharath and Shumway (2008) found out that na¡ve prediction indicator was better than hazard models, and this indicator performed better than Merton DD model and reduced-form model in terms of out-of-sample forecasts.

## 3. Theoretical development and methodology

FDP models will normally be divided into structural model and reduced form model. The structural model considers default as when a company¡s asset is relatively lower than its liabilities, and estimates the risk of default by using structural datas including asset value, the relative variation of liability and equity, etc. Regard all events of default as endogenous variables and others as exogenous variables. The examples of structural models include Merton **(**1974) model, KMV model, CreditMetrics models and others. Structural model has some assumptions that asset value obeys geometric Brownian motion and the issuing of single zero-coupon bonds. If the model¡s estimation is broadened, we can construct a reduced form model that predict with more accuracy. Reduced form model is a simplified structural model. It neglects variables like asset and equity values, which are difficult to obtain, and only remains variables on liabilities. In addition, the default is assumed as exogenous variable instead of endogenous variable. Examples of reduced form models are Credit risk+ and Creditportfolio view model.

As discussed above, this research examines the assumptions by testing statistical and economic significance of the Merton DD model default probability (π_merton), a simplified alternative probability of Shumway (π_shumway) and revised alternative probability of π_shumway. Giving explanations on models (including Merton DD, Logit and Hazard Model) before the empirical examination.

#### A. Merton DD model

Merton uses the option pricing theory presented by Black and Scholes and applies the theory to the measurement of credit risks. Merton considers the enterprise leverage is equivalent to shareholders¡ long call to the creditor. The call index of underlying asset is the company¡s asset value, and the exercise price is the liability. When liability is due, if the market value of corporation asset is lower than liability value, shareholders will choice default, and the probability that the asset can not pay off the liability is called probability of default. Merton model uses the given equity market value and variation to estimate corporation asset value and volatility, then evaluate company¡s probability of default and distance-to-default.

The distance-to-default calculates the closeness between company¡s asset and the default point, which refers to a company¡s asset value benchmark at the time of default. If the company¡s asset value is lower than its liabilities when liabilities are due, this condition will be defined as default. However, KMV discovers that the company still has capability to re-finance, so default will not happen immediately at the time when asset value is lower than the book value of liability. According to KMV¡s observation, the real default point situates between total liability and current liability. In other words, the company will default when asset value is lower than default point. To measure the risk of default, KMV combines three determining factors (asset value, asset risk and leverage), which affect probability of default, into one measurement variable: Distance to default (DD).

The distance to default indicates the distance between a company¡s asset value and default point and uses asset volatility to measure and standardize the distance; in other words, the standard deviation number between a company¡s asset value and default point, and the standardized distance to default helps a company to compare with others. Larger standardized number represents asset value is further away from default point and the expected default frequency (EDF) of this company is smaller.

The Merton DD model uses the classical bond pricing model created by Merton (1974) to estimate the market value of liability. The Merton model has two important assumptions: The first is that the total value of a company must comply with the geometric Brownian motion,

$$dV = \mu V dt + \sigma_V V dW, \tag{1}$$

where V represents company¡s total value; £ is the continuously expected of compounded return on V; σv is volatility of the company¡s asset value; dW is comply with standard Wiener process.

The second assumption of Merton model assumes a company issues a discount bond, which is due on time T. Under those two assumptions, shareholder equity is a call option on the underlying value of a company with a strike price equal to the face value of company¡s liability with due date T. Thus, the formula for shareholder equity and company value is called Black-Scholes-Merton Formula. In the put-call parity, the value of company liability is equivalent to the value of a risk-free discount bond deduct the value of a put option written on company asset, and a strike price equal to the face value of liability with due date T.

The company shareholder equity value of Merton model complies with the formula below:

$$E = V\mathcal{N}(d_1) - e^{-rT}F\mathcal{N}(d_2), \quad (2)$$

E represents the market value of the company shareholder equity; F is the face value of company liability; r is the synchronized risk-free rate; N(.) is the cumulative standard normal distribution function; d1 is the formula below; and d2 is just $d_1 - \sigma_V\sqrt{T}$.

$$d_1 = \frac{\ln(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}, \quad (3)$$

The Merton DD model makes use of two important formulas: The first is the Black-Scholes-Merton formula (2) indicating the value of company shareholder equity as a function of company value. The second formula relates to the volatility of the company value to volatility of shareholder equity. Under Merton¡s assumption the shareholder equity is a function of company value and time, so it is directly complied with Ito¡s lemma:

$$\sigma_E = \left(\frac{V}{E}\right)\frac{\partial E}{\partial V}\sigma_V. \quad (4)$$

In the Black-Scholes-Merton model, it is certified that $\frac{\partial E}{\partial V} = \mathcal{N}(d_1)$, and complies with the assumption of Merton model, which the volatilities of company and shareholder equity can indicate as:

$$\sigma_E = \left(\frac{V}{E}\right)\mathcal{N}(d_1)\sigma_V, \quad (5)$$

and dl is defined in formula (3).

The target of this research, NPO (Credit unions), do not collect capital by issuing shares to the public; the capital is only combined by internal members¡ deposit. Thus, when defining the volatility of shareholder equity, the data cannot be collected according to the estimated condition of original Merton model. In order to calculate the volatility, stock price (Pt) is replaced only by net income per month divide by deposited shares. Separating the effect of global financial distress to the equity volatility, this calculation basis of equity volatility is divided into monthly data before 2007 and after 2008.

The Merton DD model basically uses two nonlinear equations (2) and (5), and transfers the value and volatility of company shareholder equity into the implied probability of default. For most applications, the Black-Scholes-Merton model describes functions of strike price, due date, underlying asset value and risk-free rate, which are unable to observe value by option, and one volatility variable still need evaluation. In the Merton model, the value of option can be observed from the value of company equity, but the underlying value of company asset can not be observable. Therefore, the fact that V infers E can be observed from market data (number of company¡s outstanding share multiple by current stock price). Similarly, equity of volatility needs to be estimated, and volatility of underlying asset price must be calculated in the Merton DD model.

The first step in implementing the Merton DD model is to estimate $\sigma_E$ from the data of historical stock returns or optional implied volatility. The second step is to choose the prediction period and to measure the face value of company liability; for example: Using historical stock returns data to estimate the equity volatility, assuming the prediction period is one year, and making the book value of company total liability equals to the face value of company liability. The third step is to collect risk-free rate data and the market price of company equity. After applying the three steps above, we gain the values of various variables (except for V and σv) for the formulas (2) and (5). The forth step is the most obvious, which is to solve V and σv of formula (2). The distance to default can be displayed with the formula below:

$$DD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}, \quad (6)$$

£ is the estimate for the expected annual return of company asset. The implied probability of default is expected default frequency (EDF), which can be written as:

$$\pi_{\text{Merton}} = \mathcal{N}\left(-\left(\frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}\right)\right) = \mathcal{N}(-DD). \tag{7}$$

If assumptions of the Merton model are agreed, then Merton DD model can forecast the accurate probability of default. As matter of fact, if the Merton model¡s assumptions can be ensured, the implied probability of default should be presented as π_merton, which is a valid statistic for the prediction of default. Therefore, this research will firstly examine this assumption.

It is rational and direct to solve formulas (2) and (5) at the same time; however, Crosbie and Bohn (2003) claimed that the effect of market leverage will lead the solution of formula (5) into irrational result. Crosbie and Bohn (2003) and Vassalou and Xing (2004) provided a complicated method to solve the problem: First, we assume the initial value is $\sigma_V = \sigma_E[E/(E+F)]$, then use σv to infer the market price of daily company asset of the previous year from formula (2). We will calculate the implied return of daily assets and use this series of returns to find the new estimated value of σv and μ. Calculate the σv repetitively, until the convergence is smaller than 0.001. This procedure gains the value of π_merton and use formula (7) to calculate the relative implied probability of default.

**Simplified Alternative Probability (π_shumway)**

To examine whether π_merton is beneficial for reduced-form models, we follow the research of Bharath and Shumway (2008) and construct a simplified alternative probability (π_shumway), without solving the formulas (2) and (5) like the Merton DD model does above. The construction of π_shumway has two purposes: First, providing the same datas as the Merton DD model, we hope π_shumway has the same forecasting ability as π_merton and becomes the functional form of π_merton. Second, hoping π_shumway is a simplified in order to avoid solving formulas or complicated estimation. The estimation or optimization of π_shumway is listed below.

Before the construction of π_shumway, we first assume the market price of each company¡s liability is equal to the face value of its liability.

$$\text{Shumway } D = F \tag{8}$$

If the liability risk of a company increases, it is closer to the point of default and bankruptcy. If the risk of liability is related to the risk of shareholder equity, the volatility of each company¡s liability can be shown as:

$$\text{Shumway } \sigma_D = 0.05 + 0.25 * \sigma_E. \tag{9}$$

In conclusion, the term structure volatility can be set as 5%. In addition, the factor of equity volatility can be set as 25%, so the combined volatility and default risk are related. The total volatility of a company can be shown as:

$$\text{Shumway } \sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25 * \sigma_E). \tag{10}$$

Afterward, we assume the expected return of company asset is equal to the stock return over the previous year.

$$\text{Shumway } \mu = r_{it-1}. \tag{11}$$

In order to use the return datas of the previous year to simplify the estimate of £, we take the model similar to the Merton DD model and simplify the distance to default (Shumway DD), which can be shown as:

$$\text{Shumway DD} = \frac{\ln[(E+F)/F] + (r_{it-1} - 0.5 \text{ Shumway } \sigma_V^2)T}{\text{Shumway } \sigma_V\sqrt{T}} \tag{12}$$

This simplified alternative model is easy to calculate, retains the structure of the Merton DD distance to default and expected default frequency. It also maintains the same method as the Merton DD model. Using this method can be helpful for the Merton model solving and calculate π_merton. The further estimation of simplified probability is:

$$\pi\_\text{shumway} = N(-\text{shumway DD}) \tag{13}$$

Commenting on π_shumway is simple, because the term structure and equity volatility can be set according to different imitations of data characteristics. We want to construct a predictive tool with simple calculation and significant statistical results. If π_shumway has the same predictive result as π_merton, we can still carefully construct a probability, which has better predictive result and covers the same scope of data.

This method takes the π_shumway according to the setting value of term structure and equity volatility, and develops four simplified probabilities. Those simplified probabilities define π(term structure volatility, equity volatility), such as π_α_up (0.5,0.25)、π_α_down (0.005,0.25)、π_β_up (0.05,2.5)、π_β_down (0.05,0.025). By using the estimation of simplified probability mentioned above, the predictive description for the financial distress of Credit Unions will be more suitable. The suitable settings for the Credit Unions can be found through the examination on the data characteristics of Credit Unions (NPO) and companies, and the adjustment of term structure volatility and equity volatility.

**B. Logit Model**

This model investigates the relationship between dependent variables and independent variables, and regression model is often used in statistical analysis. However, if the dependent variables of regression model display binary characteristic, the strain will have two possible results (whether the company is default or not). If the ordinary least squares (OLS) method is used, the estimated value still satisfied the unbiasedness, but the problem is that it has heterogeneity in residuals item. And the model cannot guarantee the estimated values will fall between the unit intervals. In addition, the dependent variables do not satisfied the assumption of regression analysis, so the traditional regression analysis is not suitable in this case.

The Logit model was created to avoid the defect mention above. This model is suitable for the regression that has dependent variable as quadratic forms. Comparing to the Discriminant analysis (DA) model, the Logit model does not follow the assumption that independent variables must obey normal distribution. In addition, the Logit model can further estimate the company¡s default probability, and the estimated model is shown below:

$$y_i^* = \beta_0 + \sum_{j=1}^{k} \beta_j X_{i,j} + u_i \qquad (14)$$

In the model, $\beta$ is the parameter to be estimated; X is the independent variable; $u_i$ is the random error term; $y_i^*$ is the variables that cannot be observed, such as credit rating of the company, which often named as latent variable. We can use the dummy variable $y_i$ as the substitute variables of $y_i^*$; for example, $y_i = 1$ when a company default, otherwise, $y_i$ =0. This is shown below:

$$y_i = \begin{cases} 1 & \text{if} \quad y_i^* > 0 \\ 0 & \text{otherwisw} \end{cases} \qquad (15)$$

According to the formula above, we can define the probability ( $P_i$ ) when $y_i = 1$:

$$\begin{aligned} P_i &= \Pr ob(y_i = 1) = \Pr ob\left[\ (u_i > -(\beta_0 + \sum_{j=1}^{k} \beta_j X_{i,j})\ \right] \\ &= 1 - F\left[ -(\beta_0 + \sum_{j=1}^{k} \beta_j X_{i,j}) \right] = F\left[ \beta_0 + \sum_{j=1}^{k} \beta_j X_{i,j} \right] \end{aligned} \qquad (16)$$

F is the cumulative distribution function of $u_i$, and we can present the likelihood function as:

$$L = \prod_{y_i=1} P_i \prod_{y_i=0} (1 - P_i) \qquad (17)$$

In the Logit model, if the function F obeys the logistic distribution as the formula below, we can use the maximize likelihood method to calculate the parameter values ($\beta_i$).

$$F(Z_i) = \frac{\exp(Z_i)}{1+\exp(Z_i)}, \quad Z_i = \beta_0 + \sum_{j=1}^{k} \beta_j X_{i,j} \tag{18}$$

Since this model assumes the cumulative distribution function of residuals also follows the logistic distribution; thus, the probability transfer function below ensures that the estimated probability will fall between 0 and 1:

$$P_i = \frac{\exp(Z_i)}{1+\exp(Z_i)} \tag{20}$$

**C. Hazard Model**

Wheelock and Wilson (2000) pointed out that the estimation of hazard functions is used when researching the model of the factors of default or merger/acquisition in American banking industry. Goddard et al. (2008) also used the hazard functions to calculate the risk value of merger and acquisition or bankruptcy for Credit Unions in U.S..

The analysis technique of the Hazard functions or Survival functions is often used in the data of lifetime distributions, and this analysis technique applies to the dynamic statistical tools in order to analysis the time of certain event. Thus, using this technique as Financial Distress Prediction (FDP) model is different from other traditional model. While other analysis techniques focus on the error cost of classification, the technique of Survival functions focuses on the lifetime distributions, which represent the distribution of random variables of non-negative number and the lifetime of the individual sample within the parent. The Survival functions S(t) represent the probability for a company to remain survive at time t; the Hazard functions h(t) also represent the probability for a company to synchronously close down at time t.

Previous researches were more interested in comparing the survival result of two or more groups. For instance, in the default research of company bankruptcy, the different operating methods between ordinary companies and bankrupted companies were compared. However, under most cases, the individuals within a group sometimes have extra features that may affect the research result. For examples, variables like ROA and the equity pledge ratio of shareholders can be seen as the covariance (explanatory variables) of survival time. After the adjustment of those potential explanatory variables, the comparison on survival time or probability of default bankruptcy will have fewer biases.

In the survival analysis, the most important regression analysis that often used is the Cox pro-portional hazards model, which is simplified as Cox model:

$$\lambda\{t|\bar{X}(t)\} = \lambda_0(t)\exp\{\beta X(t)\} \tag{21}$$

$$\bar{X}(t) = \{X(s) : 0 \le s \le t\} \tag{22}$$

All covariate history of the research target before time t; β is relative to the regression coefficient of covariance X(t); λo(t) is the unspecified baseline hazard function. In this model, the baseline hazard function can be explained as an individual¡s risk function that appears to have 0 for all covariance values at time origin, and it remains same value over time changes. In other words, the bankruptcy and default risk without effect from any covariance. The covariance X(t) and time t are interdependent. The regression coefficient β can explain the increased amount of logarithm risk function of two individuals at time t, and the integral of risk function can gain the survival function of individual number i.

$$S_i\left(t|\bar{X}(t)\right) = \exp\left[-\int_0^t \lambda_0(u)e^{\beta X_i(u)}du\right] \tag{23}$$

This survival function does not only attach with unspecified baseline hazard function λo, but also relates to the time interdependent covariant value within the time interval [0, t].

**D. Comparison of Models**

The differences among Merton DD, Logit and Hazard Models are concluded as follows:

1. Most of previous literatures used the Merton and KMV model to investigate the company¡s predictive capability of financial distress, but the result shown that the predictive capability of financial distress was poor. To determine a company when will have financial distress, the Merton model uses the standard of total asset below total liability to, and the KMV model uses the standard of total assets below the sum of current liability and half long-term liability. However, literature reviews discover that both models¡ definition of default do not met the default events like bounced check, run on bank, relief and help, suspension due to financial distress. Those events are classified as the phenomenon of insufficient liquidity during operation, rather than a bankruptcy, which has more strict definition. As matter of fact, many companies¡ financial crises are difficulty of operation such as too much inventory, too many payable accounts and difficulty of capital management. Those difficulties reflect the short-term categories on financial reports, including the change of current assets and current liabilities. The biggest difference between the Merton DD model and other models is that Merton DD model has daily hazard measurement period, which can follow market condition at any time, and precisely controls the credit hazard change of asset positions. In addition, the Merton DD model does not concern the data of credit rating, but uses the financial and stock data of individual companies to calculate the company¡s expected default frequency. This improves the accuracy of the model forecast and the data used as variables are easier to find. The Merton DD model uses option valuation theory to evaluate a company¡s credit hazard and it assumes that the change of company¡s asset value is displayed in normal distribution during the process. However, the empirical result shows that the loss distribution of company¡s default events is often non-normal, and the Merton DD model only assumes the occurrence of default events when the liabilities are due, which is irrational; those two situations disagree with the assumption of the Merton DD model. When a company is facing closure, the asset value might tighten rapidly due to the reason of quick disposal, or the company might try it best to adjust the proportion of liability and asset during the financial distress. Thus, the consideration the volatility of liability is more practical method.

2. Comparing with the traditional MDA model, the Logit model does not have the assumption of variable distribution method. Thus, the empirical research does not need to concern whether the variable distribution method obeys normal assumption or not. In addition, since there is no problem of normal assumption, the Logit model can use dummy variable to do the regression research. The model has more options for the set of variables and finds the most suitable explanatory variable. Logit was originally evolved from the linear probability model, which can evaluate the probability of events. However, the biggest defect of the linear probability model is that the probability of event will be larger than 1 or smaller than 0, because the model uses the linear method to do the regression evaluation of the event probability. The result of the event fits in a straight line, so the result might exceed the restriction scope of probability, which is an irrational probability result of default estimation. The Logit model uses the linear regression method to calculate the event probability and then transfers the result with the logistic distribution, so the final probability obeys the form of probability and remains the original regression result. Therefore, empirical researches use Logit model instead of the linear probability model.

3. The Logit model improves the defect of nominal variables processing and distribution assumption of MDA model; however, Logit model still can not provide the default probability (or survival rate) of the research target at different time in the future. Using a survival analysis (widely used in medical field and actuarial field) as the foundation, establishing a complete company hazard data research and conforming the implementation applicability of this research. The advantage of Hazard model (hazard and survival analysis) is the ability to forecast the time point close to default. Although the Logit model can predict the default probability for a period in the future, it is unable to predict the time point close to default and it lists the company as dangerous before the existence of default hazard, which loses important customers easily. In contrast, the survival analysis forecasts the time point close to default and the future time when a company has a high hazard condition of default. Previous literature shown that Cox model has less type I error, which also reduces the credit error loss of financial institutes. Since more significant variables can provide more accurate information for prediction, the usage of survival model is suggested. Therefore, different models evolve according to different characteristics of research data and provide wide usage scope and smaller assumption restriction. The Merton DD model concerns the real-time data of market; the Logit model has its practicability and efficiency; the Hazard Model predicts the time point of default according to the variation over time. Thus, different models have their scope and restriction of usage, which depend on the purpose of research and the form of data.

## 4. Data and Model Specification

The major goal of this study is to apply the FDP models, such as Merton DD model, Hazard model, and Logit model to conduct empirical research and based on the selection of variances, explaining abilities, and prediction accuracy to select the target models. By analyzing the data of Taiwan¡s Credit Unions, the study makes a comparison between the data of Taiwan¡s Credit Unions and other default forecast literature researches which are relevant to Credit Unions or companies and organizations in order to see if there is any difference.

### A. Data and sample selection

First of all, we adopt the data of Taiwan¡s Credit Unions to process model estimation. The datas of financial and organizational variables were retrieved from Credit Union League of the Republic of China (CULROC), and the time period was from January, 2001 to December, 2009, retrieving the Panel datas of all Credit Unions in every month and every year, and using different default estimation models to predict the possibility of financial distress in those Credit Unions.

Normally, full-cash delivery stock, suspension, and closure and bankruptcy announcement are the starting points to determine financial distress, but as the operations of some companies are deteriorating, they are not discovered to have encountered financial distress until the cause bursts out, which is a great harm to stakeholders and investors. The definition of financial distress in Taiwan Economic Journal (TEJ) includes 16 default events（Note1）, which are more worth referring than previous events, and thus this study adopts its definition. Financial distress can be divided into 2 categories: financial distress and quasi-financial distress ; the difference lies in that quasi-financial distress has not encountered financial distress, but the possibility of financial distress burst-out is quite high in the future; thus, it is included in financial distress.

The variables needed in financial distress prediction model (refers to Table 1.) include 22 variables such as asset size, profitability, asset quality, risk, managerial efficiency, growth, macro factor, asset volatility, and Expected Default Frequency (EDF), etc. In addition, three variables such as age, region type, and common bond of Credit Unions are targeted and discussed.

In the end of 2001, among the 307 pieces of information provided by CULROC, 10 of them were reported to have financial distress, while among the 314 pieces of information retrieved in the end of 2009, 53 of them were reported to encounter financial distress. During the time period, there are 2,793 effective samples, and the number of samples facing financial distress is 333 in total.

### B. Sample selection

When discussing which covariates of hazard functions to choose to forecast financial distress in Credit Unions, we do sample statistics explanation for each covariate, and Table 2 shows the means, standard deviations, and correlation coefficients of the time-varying covariates in hazard functions model. To calculate and illustrate these statistics data, we need to arrange the yearly sample data of every Credit Union between 2001 and 2009 into pooled panel datas. The more significant result is that the distribution of expected default frequency (π_merton) calculated by the Merton DD model is similar to the distribution of simplified linear combination probability (π_shumway). The estimated mean of π_merton collected from 2001 to 2009 is 8.835%, which is lower than 10.95%, the mean collected from 1980 to 2003 and calculated by Bharath and Shumway(2008), but it is higher than the mean calculated during 1971 to 1999: 4.21%, which was done by Vassalou and Xing(2004). The correlation coefficient of the expected default frequency between the Merton DD model and simplified model is 41.8%, which is statistically significant if under 1%; the distributions of asset volatility of the Merton DD and simplified models are similar as well, with correlation coefficient reached 43.9%.

Table 3 shows descriptive statistics of none time-varying covariates, and the descriptive statistics respectively illustrates the distributions by year of formation(age), region(region type), and relationship(common bond) of all the Credit Unions with or without financial distress. Table 4 indicates the sample means of time-varying covariates collected from 2001 to 2009, including the datas of all the Credit Unions. And Table 5 points out the sample means of time-varying covariates from 2001 to 2009, including the data of all the Credit Unions that were under normal operation and those faced financial distress.

Empirically, the literature and theories about banking business had significant relationship with asset scale and performance; from economic scale, loan business, to monitor system, all these make large financial institutions request lower cost and higher requirement. Likewise, it means small-scale Credit Unions own higher risks of confronting financial distress than larger-scale institutions. We discovered that in Table 6, the LASSET of hazard functions possesses negative coefficient, and the mean of sample asset of Credit Unions in Table 4 shows a slow increase during sample period; besides, in Table 5 it shows that the mean of asset scale of financially distressed Credit Unions is obviously below the mean of Credit Unions which do not distressed.

The π_merton of expected default frequency (EDF) in Table 4 is around 8% from 2001 to 2007, and it increased to 10% after 2008; the distribution of π_shumway had been shifting between 14% and 17% before 2007, while in 2008, it went up to 19%. Based on the adjustment of the volatility of term structure and equity, the market¡s equity volatility formed 4 EDF values, and only the distribution of π_β_down value closes to the distress rate in Table 4; σv_merton has little change and only bounces between 34% and 35%; the distribution of σv_shumway value before 2007 is between 27% and 29%, while it climbs up to about 31.5% after 2008. Viewing distress rate as the foundation, π_merton is slightly underestimated, and π_shumway is overestimated that still has space to revise down its value; in Table 5, each EDF and volatility of financially distressed Credit Unions is clearly higher than Credit Unions which do not distressed.

Note 1: Financial distress includes the following nine situations: bounced check, bank run, shutdown and bankruptcy, CPA opinion (for instance, accountants hold negative opinions toward the continuous operation, or they doubt the assumption of continuous operation.), rearrangement, asking for bailout (but if a company only requires interest decrease, it is not financially distressed), taking over, total delisting( exclude companies whose book value per share is less than 5 dollars), work stoppage because of financial problem, negative net worth, etc. Quasi-Financial distress include the following seven situations: appropriating and draining company fund, temporary shutdown, bounced check by the president of a company, shrinking banks, severe deficit, work stoppage because of economic downturn, and decrease of value, etc.

In Table 4, the increasing of each financial variable mean from 2001 to 2009 indicates capital adequacy ratio (CAP_ADE), liquidity ratio (LIQ), the reserves capacity for loan ratio (RES_CAP), and labor cost ratio (LAB_COST), while decrease shows loan ratio (LOAN_RATIO), income capacity rate (INC_CAP), stock return ratio (STO_RET), ROA, business growth rate, and overall economic variables, etc. Table 5 shows that normally operated Credit Unions have better liquidity ratio (LIQ), labor cost ratio (LAB_COST), the coverage rate of overdue_loans (LOAN_COV), operating expense ratio (OPE_EFF), income capacity rate (INC_CAP), ROA, and each business growth rate, etc.

In Table 6, LAGE has certain degree of correlation with organization scale, but LAGE coefficient has no significance in eastern area and single common relationship, and this indicates that newly founded Credit Unions have high risks. The distribution of ages of the entire sample Credit Unions in Table 3 are slightly different from the ones with financial distress. The financially distressed Credit Unions were mainly established between 1971 and 1980, but between 1991 and 2000, the number of Credit Unions founded had increased.

In the analysis of profitability, the negative ROA coefficient in hazard functions indicates Credit Unions of low profitability are more intended to confront financial distress than those of high profitability. In fact, averagely, the ROA of financially distressed Credit Unions tends to be lower than the Credit Unions which do not distressed.

As for financial risks, Credit Unions with high liquidity (LIQ) have lower risk in encountering financial distress than those with low liquidity, and this shows the importance of current asset to operation. But liquidity ratio was not as significant to the single common bond, the Credit Unions in eastern area, and the period from 2004 to 2009. It shows that Credit Unions with higher loan ratio have lower liquidity ratio, and some engaged in short-term financial investment after 2004. High RES_CAP represents the degree of risk tolerance when handling loan business, and shows significant direct relationship. Under the circumstance that loan business keeps shrinking, Credit Unions with low reserves capacity for loan ratio elevate the ratio, and Credit Unions depending on loan interest margin will face a rapid drop of profitability. Although loan default risk tolerance has increased, it increases the chances of encountering financial distress.

In terms of asset quality, usually when compared with other financial institutes, Credit Unions tend to be limited by asset accumulation and not easy to expand their scales, because Credit Unions cannot issue stocks to raise fund, they solely depend on the share-deposit of their members and utilize each reserve and retained earnings, etc. In hazard functions, the capital adequacy ratio (CAP_ADE) mostly has inverse relationship, which means that capital ratio tends to be lower and risk be higher, but the coefficient estimation is insignificant in the single common bond and eastern area. Loan asset has lower liquidity and higher risk than other assets; therefore, Credit Unions with higher loan ratio tend to have higher risk of financial distress, but loan ratio is insignificant in hazard functions, and higher loan ratio guarantees interest income, which can lower operation risk; LOAN_COV is also insignificant, and it means that although coefficient shows low loan ratio and LOAN_COV would increase the chances of confronting financial distress, it is indeed insignificant in empirical estimation.

For management efficiency, to measure cost efficiency in an organization depends on how much operation fee takes up the total asset. Credit Unions with little efficiency usually tend to face financial distress, and in hazard functions, the operating expense ratio (OPE_EFF) has high direct relationship, which indicates that the higher the operating expense ratio, the higher the risk of financial distress. Ratio of personnel expense also has highly significant direct relationship, and it means that the higher the labor cost ratio (LAB_COST), the higher the risk of financial distress. Even though the ratio of income capacity (INC_CAP) presents an inverse relationship, which shows higher risk with lower ratio, it is insignificant to Credit Unions, except for those with single common bond.

In terms of the increase of each part, including the number of members, loan, and money paid for shares, the increase of the number of members is significant only to Credit Unions with single common bond, and the rest are not. The growth of loans shows clear direct relationship with Credit Unions in western area, which indicates high growth rate on loans shows high risk. The growth of the money paid for shares shows insignificant direct relationship to Credit Unions with multiple common bond and eastern area, which shows the higher the growth rate, the bigger the pressure for capital utilization, so if capital has not been properly utilized, the chances of having financial distress will increase.

For overall exterior environmental factors, only the spreads from deposit and loan in banking business shows a significant inverse relationship in hazard functions, so the smaller the spreads from deposit and loan in banking industry, the higher the risk for Credit Unions to have financial distress. With such convenient loaning and financing channels, lenders can choose banks instead of Credit Unions, and that makes the loan business in Credit Union shrink and its overall earnings is dropping as well. The other three overall variables have no significant relationship, while as Table 5 shows, 2008 and 2009 were the times when financial tsunami struck, and the annual growth of average interest rate of deposits (RATE), the spreads from deposit and loan (RATE_SPR), GDP, and M1b has reached a historical low, and the rate of financial distress also increases.

Common bond is the requirement for the members in Credit Unions to enjoy corresponding services, and in hazard functions, MUT is a dummy variable to differentiate single and multiple common bond; in addition, EAST is a dummy variable to differentiate eastern and western Credit Unions. The descriptive statistics in Table 3 shows Credit Unions with single common bond have higher risk to encounter financial distress, while this is not the case for eastern and western Credit Unions.

## 5、Empirical evidence&Results

### A. Models estimation results

The empirical results are shown in Table 6 and Table 7, including the default estimation of each model and their adjusted R-squared, etc., and we adopted the pooled panel datas to estimate the fixed effects of research sample, Hausman test was also used to examine the random and fixed effects of the models, and the results are all significant; we choose fixed effects method to conduct estimation.

In Table 6, Equation I, II, and III are based on the data of Credit Unions, which is collected from the time periods of 2001 to 2003, 2004 to 2006, and 2007 to 2009, and Equation I and II show that the only the same significant variables are labor cost ratio (LAB_COST) and GDP. In Equation III, hazard functions estimates that between 2007 and 2009 was the time when financial tsunami struck, so there are seven variables that show significance, which is much more than the time period of 2001 to 2006, and Equation III possesses better explanation ability than Equation I and II. Interestingly, most EDF values in Equation I, II, and III are insignificant.

In Equation IV, Hazard functions estimate every situation of all the covariates, and in Equation V and VI, the estimation contents are copied from Equation IV, but the data adopted is respectively the data of eastern and western Credit Unions; finally, Equation VII and VIII respectively adopt single and multiple common bond in Credit Unions. In Equation IV, the value of $\pi_\beta$_down is more statistically significant than $\pi$_shumway and $\pi$_merton, and thus we can prove that the first assumption previously mentioned is invalid. The results also show that ROA is statistically significant, but the value of $\pi$_merton, though adopted the same financial data, is insignificant; Therefore, the insignificance of π_merton indicates that it is needless to seek the functional form of sophisticated equations, and this helps reverse the third assumption. We in effect need not to calculate asset value and volatility of companies in the Merton DD model.

From Equation V to VIII, their coefficient of $\pi$_merton and π_shumway is mostly insignificant, while the value of π_$\beta$_down shows significance in the overall data, eastern data, and data collected between 2001 and 2003, and thus we reconfirm that the first assumption is invalid; In addition, the proper probability setting for Credit Unions is different from the assumption of π_shumway, so it still has space to revise down the coefficient of equity volatility. Previous statement shows that the value of the Merton DD model is to get a functional form, instead of a detailed functional form of this model.

In the estimation of hazard functions, asset scale and expected financial distress risk presented an inverse relationship that the coefficients of LASSET are negative, and most of them show significance. When it comes to LAGE coefficient, only the data of Credit Unions in eastern area and single common bond is insignificant, which shows that early established Credit Unions possess higher risk. And in terms of profitability, earning power and expected financial distress risk present an inverse relationship, and the coefficient of ROA is negative; besides, except eastern Credit Unions and those with single common bond, the rest variables all show significance.

As for asset quality, generally, most CAP_ADE value shows significant inverse relationship, and it also indicates that the lower the capital adequacy ratio, the higher the risk, but the only insignificant coefficient is the coefficient of eastern and single common bond Credit Unions. Surprisingly, the loan ratio and the coverage rate of overdue_loans in each part, and Table 4 and Table 5 show that financially distressed Credit Unions tend to have lower ratio. In the part of financial risk, LIQ has significant inverse relationship in coefficient estimation, except for the coefficient value of 2004 to 2009, Equation V in eastern area data, and Equation VII in single common bond. The reserves capacity for loan ratio (RES_CAP) shows a direct relationship in coefficient estimation, which means asset liquidity, the reserves capacity for loan ratio (RES_CAP), and financial distress risk possess the quality of low liquidity with high risk, and the high reserves capacity for loan ratio (RES_CAP) with high risk.

For management efficiency, the financial distress risk and operating expense ratio have highly significant direct relationship; likewise, labor cost ratio (LAB_COST) also has high significant direct relationship, while the income capacity (INC_CAP) shows significant inverse relationship only with Credit Unions with single common bond. And for business growth, most growth rates present insignificant relationship. For the overall external environment factor, the spreads from deposit and loan of banking industry (RATE_SPR) have significant inverse relationship, except in the eastern are of Equation V and the single common bond of Equation VII, and the rest of three variables have no significant relationship.

### B. Out-of-sample Forecasts

Table 7 shows the estimations and forecast results of empirical models, including the coefficient estimation on each variable, Adjusted R-squared, and Root Mean Squared Error (RMSE) of Model I to model VIII, etc. The time period chosen to conduct out-of-sample forecasts is between 2008 and 2009, collecting the RMSE value to compare the actual and expected value of each model and further assesses their predictive capability.

Equation I and II are the estimation of single variable hazard models, including the explanation for time-varying $\pi$_merton and π_shumway estimation, and Equation I and II show that $\pi$_merton and π_shumway are variables with statistical significance, especially the four simplified probability values in Equation II, which are based on the setting of π_shumway that is modified by term structure volatility and equity volatility in time periods. Two of the simplified probability values show significant direct relationship with the risk of financial distress, the coefficient and standard deviation of π_β_down (0.05,0.025) are especially closer to the estimation of π_shumway, which means that the equity volatility of Credit Unions is lower than the stock volatility of general companies, and the result also qualified the non-profit characteristics of Credit Unions. In Equation III, hazard models simultaneously estimate π_merton, π_shumway, and the four simplified probability estimation values; Four of these values are significant. Although π_merton is significant, it does not match the assumption that indicates high π_merton with high possibility of financial distress, while the direction and intensity of π_shumway coefficient are smaller than Equation II, and without significance, and that means the setting of expected default frequency of Credit Unions can adjust the equity volatility coefficient of π_shumway, and reducing the value of π_β_down could make Equation II has significance, presenting direct relationship and highest intensity, which matches the assumption that high default probability also has high risk. Hence, we can reach a conclusion that π_merton and π_shumway are not correct and most efficient instruments to predict default probability.

When coordinating out-of-sample forecast models with financial and organizational variables, π_merton and π_shumway are shown as model IV and model VI. The π_merton in model IV is statistically insignificant, and the π_shumway of model VI is statistically significant, as well as π_β_down. In model VII, only π_β_down shows significance, and π_merton and π_shumway are insignificant; In addition, the predictive capability of model VII is more significant than model I, II, and III, which are the models simply taking account of the default probability of market equity volatility. The result matches the research done by Vassalou and Xing (2004) and Bharath and Shumway (2008). π_merton offers more than the predictive capability of market equity, and it obviously also provides an instrument to measure probability, and to construct a linear combination to calculate expected default frequency. While π_β_down is more statistically significant than π_merton and π_shumway on hazard models and out-of-sample forecast. The probability value offered by Merton DD model is more economically valuable than its functional form.

Model VIII is a logit model considering all the variables, and we can clearly tell that the number of significant variable in hazard model is more than logit model, which also matches the conclusion proposed by previous literature research. Therefore, model VII has better results than other models no matter on the number of the estimation of significant variables, the explanation of models, or out-of-sample forecast.

## 6. Conclusion

First, we are examining the accuracy and contribution of Merton distance to default (DD) model. After the empirical test of hazard models, we discover that π_merton does not possess significant predictive capability on default probability. Considering other default predictive variables will improve the π_merton, we discover the π_shumway, constructed in z-score form, can improve predictive capability; the predictive capability can be improved more if the strength of equity volatility can be adjusted to lower status. For the predictive capability of out-of-samples, the performances of uni-prediction index like π_merton and π_shumway or Logit model are poorer than the hazard models, which add π_β_down.

The estimated performance of hazard functions has significant relationship to the risk of financial distress generated by credit unions; this includes the assets size, profitability, capital adequacy ratio, liquidity, the reserves capacity for loan ratio in financial risk, operating efficiency, labor cost ratio, share capital growth rate in management efficiency, and the spreads from deposit and loan in banking industry of the holistic exterior environment. The future research can do further investigation on the issues mentioned above.

Focus on the differences of financial distress prediction between profit-making companies and non-profit organizations (NPO; credit unions). Normally, profit-making companies have ratings from the credit rating agencies; however, NPO do not have credit ratings from relative professional agencies and their financial operation normally remain private. If financial distress occurs in NPO, it is often irreparable. Verifications of the models mentioned above provide NPO with a common operating model, which predicts financial distress. Thus, different models are improved by the research data with different characteristics, and some models have broader scope of application and smaller hypothesis restrictions. The Merton DD model concerns the real-time market data; The Logit model has practicability and convenience; The Hazard model considers the changes according to time and predicts the time point of default. For the profit-making companies and non-profit organizations, different organization characteristics suit different models. FDP, which can prevent Credit Unions from financial distress, is a model combined Hazard model with corrected Merton DD, and it can reflect market volatility information in real-time and predict the time point when distress occurs.

## References


Altman, E.I., 1968. Financial ratios, discriminant analysis, and the prediction of corporate bankruptcy. Journal of finance 23, 589¡609.

Beaver, B., 1966. Financial ratios as predictors of failure. Journal of accounting research autumn, 91¡101, Empirical research in accounting: selected studies, supplement.

Beaver, B., 1968a. Alternative accounting measures as predictors of failure. Accounting review January, 113¡122.

Beaver, B., 1968b. Market prices, nancial ratios, and the prediction of failure. Journal of accounting research Autumn, 170¡192.

Black, F., M. S. Scholes, 1973. The pricing of options and corporate liabilities. Journal of political economy 81, 637¡659.

Bharath, S., Shumway, T., 2004. Forecasting default with the KMV-merton model. Working paper, University of Michigan.

Bharath, S., Shumway, T., 2008. Forecasting Default with the Merton Distance to Default Model. Review of financial studies 21(3), 1339-1369.

Crapp, H. R., Stevenson, M., 1987. Development of a method to assess the relevant variables and the probability of financial distress. Australian Journal of Management 12(2), 221-236.

Crosbie, P.J., Bohn, J.R., 2002. Modeling default risk. Technical Report, KMV, LLC.

Crosbie, P. J., J. R. Bohn., 2003. Modeling Default Risk. http://www.ma.hw.ac.uk/mcneil/F79CR/Crosbie Bohn.pdf (accessed May 2008).

Chava, S., Jarrow, R., 2004. Bankruptcy prediction with industry effects. Review of finance 8, 537¡569.

Campbell, J. Y., J. Hilscher, J. Szilagyi, 2007. In Search of Distress Risk. Journal of Finance.

Deakin, E., 1972. A discriminant analysis of predictors of business failure. Journal of Accounting Research, Spring, 167 -179.

Duf e, D., Lando, D., 2001. Term structures of credit spreads with incomplete accounting information. Econometrica 69, 633¡664.

Duffie, D., L. Saita, K. Wang, 2007. Multi-Period Corporate Failure Prediction with Stochastic Covariates. Journal of Financial Economics 83, 635¡65.

Edminster, R., 1972. An empirical test of financial ratio analysis for small business failure prediction. Journal of Financial and Quantitative Analysis 2, 7:1477-1493.

Fisher, E., Heinkel, R., Zechner, J., 1989. Dynamic capital structure choice: theory and tests. Journal of finance 44, 19¡40.

Feinberg, R.M., 2001. The competitive role of credit unions in small local financial services markets. Review of Economics and Statistics 83, 560-563.

Feinberg, R.M., Ataur Rahman, A.F.M., 2001. A causality test of the relationship between bank and credit union lending rates in local markets. Economics Letters 71, 271-275.

Goddard, J., McKillop, D., Wilson, J.O.S., 2002. The growth of US credit unions. Journal of Banking and Finance 22, 2327-2356.

Goddard, J., McKillop, D.G., Wilson, J.O.S., 2008. The diversification and performance of US credit unions. Journal of Banking and Finance 32, 1836-1849.

Hillegeist, S.A., Keating, E.K., Cram, D.P., Lundstedt, K.G., 2004. Assessing the probability of bankruptcy. Review of accounting studies 9, 5¡34.

Harvey R. Crapp, Maxwell Stevenson, 1987. Development of a Method to Assess the Relevant Variables and the Probability of Financial Distress. Australian Journal of Management 12- 2, 221-236 .

Jones, F., 1987. Current techniques in bankruptcy prediction. Journal of accounting literature 6, 131¡164.

John Goddard, Donal McKillop, John O.S. Wilson, 2008. Consolidation in the US Credit Union Sector: Determinants of Failure and Acquisition. Working Paper Series.

Kealhofer, S., M. Kurbat, 2001. The Default Prediction Power of the Merton Approach. Relative to Debt Ratings and Accounting Variables (KMV LLC).

Kealhofer, S., 2003. Quantifying credit risk I:default prediction. Financial Analysts Journal, January¡February, 30¡44.

Lane, W.R., Looney, S.W., Wansley, J.W., 1986. An application of the cox proportional hazards model to bank failure. Journal of banking and finance 10, 511¡531.

Lee, S.H., Urrutia, J.L., 1996. Analysis and prediction of insolvency in the property-liability insurance industry: a comparison of logit and hazard models. The Journal of risk and insurance 63, 121¡130.

Leland, H., 1994. Corporate debt value, bond covenants, and optimal capital structure. Journal of finance 49, 1213¡1252.

Lin, L., Piesse, J., 2004. Identification of Corporate Distress in UK Industrials: A Conditional Probability Analysis Approach. Applied Financial Economics 14(2), 73-82.

Merton, R. C., 1974. On the pricing of corporate debt: the risk structure of interest rates. Journal of finance 29, 449¡70.

Ohlson, J., 1980. Financial ratios and the probabilistic prediction of bankruptcy. Journal of accounting research 19, 109¡131.

Shumway, T., 2001. Forecasting bankruptcy more accurately: a simple hazard model. Journal of business 74, 101¡124.

Sobehart, J. R., S. C. Keenan, 1999. An Introduction to Market-Based Credit Analysis. New York: Moody¡s Investors Services.
Sobehart, J. R., S. C. Keenan, 2002. Hybrid Contingent Claims Models: a Practical Approach to Modelling Default Risk, in Michael Ong, (ed.), Credit Rating: Methodologies, Rationale, and Default Risk. New York: Risk Books, pp. 125¡45.
Sobehart, J. R., S. C. Keenan, 2002. The Need for Hybrid Models. Risk February, 73¡7.
Sobehart, J. R., R. M. Stein, 2000. Moody¡s Public firm Risk Model: A Hybrid Approach to Modeling Short Term Default Risk. New York: Moody¡s Investors Services.
Stein, R. M., 2000. Evidence on the Incompleteness of Merton-type Structural Models for Default Prediction. New York: Moody¡s Investors Services.
Schmid, F., 2006. When for-profits and not-for profits compete: Theory and empirical evidence from retail banking. Managerial Finance 31, 50-71.
Tokle, R.J., Tokle, J.G., 2000. The influence of credit union and savings and loan competition on bank deposit rates in Idaho and Montana. Review of Industrial Organization 17, 427-439.
Wheelock, D.C., Wilson, P.W., 2000. Why do banks disappear? The determinants of US bank failures and acquisitions. Review of Economics and Statistics 82, 127-138.
Vassalou, M., Y. Xing., 2004. Default Risk in Equity Returns. Journal of Finance 59, 831¡68.

Table1 Covariates definition

| Category | Covariate | Definition |
|---|---|---|
| region_type | EAST | region(west-0,east-1) |
| common_bond | MUT | single-0,multiple-1 |
| age | LAGE | log years |
| size | LASSET | log assets |
| asset_quality | CAP_ADE | capital/assets |
| asset_quality | LOAN_RATIO | loans/assets |
| asset_quality | LOAN_COV | overdue_loan_Coverage（overdue_reserves / overdue_loans） |
| financial risk | LIQ | current_assets/total_assets |
| financial risk | RES_CAP | reserves/total_loans |
| managerial_efficiency | OPE_EFF | operating_expenses/total_assets |
| managerial_efficiency | INC_CAP | total_income/total_assets |
| managerial_efficiency | LAB_COST | salaries/total_income |
| growth | MEM_GRO | membership base growth rate |
| growth | LOAN_GRO | loan growth rate |
| growth | SHARE_GRO | share growth rate |
| profitability | STO_RET | stock return |
| profitability | ROA | return of asset |
| macro_factor | M1b | money supply growth rate |
| macro_factor | GDP | annual average rate of GDP |
| macro_factor | RATE | average interest rate of deposits(local banks) |
| macro_factor | RATE_SPR | spreads from deposit and loan (local banks) |
| expected default frequency | π_merton | merton DD expected default frequency |
| expected default frequency | π_ shumway | merton DD shumway expected default frequency |
| asset volatility | σv_merton | merton DD standard deviation |
| asset volatility | σv_shumway | merton DD shumway standard deviation |

*The variables selection and definition followed by Harvey R. Crapp and Maxwell Stevenson(1987) and John Goddard, Donal McKillop and John O.S. Wilson(2008).
*macro_factor from Accounting and Statistics in Taiwan

Table 2 Summary Statistics:Time-varying covariates

Panel A：Means, standard deviations, and correlation coefficients from CULROC

| Variable | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|
| LAGE | 3.276 | 0.539 | 0.000 | 3.870 |
| LASSET | 3.705 | 0.968 | 0.400 | 7.290 |
| CAP_ADE（%） | 8.573 | 3.587 | 0.012 | 48.311 |
| LOAN_RATIO（%） | 52.910 | 18.316 | 5.583 | 95.978 |
| LOAN_COV（%） | 5.967 | 22.140 | 0.000 | 120.079 |
| LIQ（%） | 29.999 | 17.884 | 0.000 | 99.267 |
| RES_CAP（%） | 17.707 | 13.123 | 0.014 | 268.685 |
| OPE_EFF（%） | 2.778 | 1.496 | 0.020 | 30.616 |
| INC_CAP（%） | 5.214 | 2.765 | 0.045 | 75.574 |
| LAB_COST（%） | 14.690 | 8.504 | 0.000 | 80.517 |
| MEM_GRO（%） | 1.340 | 7.095 | -100.000 | 90.160 |
| LOAN_GRO（%） | -0.726 | 27.905 | -87.061 | 1062.873 |
| SHARE_GRO（%） | 2.462 | 8.711 | -57.939 | 132.582 |
| STO_RET (%) | 2.122 | 1.235 | 0.000 | 9.120 |
| ROA（%） | 2.481 | 2.341 | -23.058 | 49.318 |
| M1b(%) | 8.115 | 6.944 | -2.938 | 18.977 |
| GDP(%) | 2.392 | 3.136 | -2.492 | 6.388 |
| RATE(%) | 2.164 | 1.219 | 1.110 | 4.620 |
| RATE_SPR(%) | 2.479 | 0.473 | 1.760 | 3.150 |
| π_merton（%） | 8.835 | 19.229 | 0.000 | 100.000 |
| π_ shumway（%） | 16.709 | 18.625 | 0.000 | 100.000 |
| σv_merton（%） | 34.183 | 275.567 | 1.117 | 4897.295 |
| σv_shumway（%） | 29.126 | 107.200 | 3.974 | 1959.254 |

This table reports summary statistics for all the variables used in the Merton DD model 、the Hazard models and Logit models. The variables definition follows as Table 1. π_merton is the expected default frequency in percent and is given by formulas (7). π_shumway is calculated according to formulas (13). σv_merton is annual asset volatility. σv_shumway is calculated by formulas (10). Our sample spans 2001 through 2009, containing 33,516 monthly data of credit unions.

Panel B： Correlations

Correlations

| | LAGE | LASSET | CAP_ ADE | LOAN_ RATIO | LOAN_ COV | LIQ | RES_ CAP | OPE_EFF | INC_CAP | LAB_ COST | MEM_ GRO | LOAN_ GRO | SHARE_ GRO | STO_RET | ROA | M1b | GDP | RATE | RATE_ SPR | π_ merton | π_ shumway | σv_ merton | σv_ shumway |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LAGE | 1 | .335(**) | .304(**) | -.191(**) | -.211(**) | .045(*) | .266(**) | -.068(**) | -.132(**) | 0.021 | -.197(**) | -.247(**) | -.363(**) | -.093(**) | -.090(**) | -.054(**) | -0.017 | -.133(**) | -.153(**) | -.146(**) | 0.014 | -.231(**) | 0.006 |
| LASSET | .335(**) | 1 | -.097(**) | -.119(**) | -.116(**) | .059(**) | -0.036 | -.237(**) | -.114(**) | -.297(**) | -.137(**) | -.170(**) | -.161(**) | .131(**) | 0.036 | -0.007 | 0.003 | -.038(*) | -0.036 | -.193(**) | -0.036 | -.319(**) | -.068(**) |
| CAP_ ADE | .304(**) | -.097(**) | 1 | -0.037 | -.109(**) | -.099(**) | .552(**) | .152(**) | 0.018 | .216(**) | -.062(**) | -.084(**) | -.227(**) | -.108(**) | -.071(**) | -.109(**) | -.079(**) | -.219(**) | -.291(**) | .043(*) | .073(**) | -.075(**) | .097(**) |
| LOAN_ RATIO | -.191(**) | -.119(**) | -0.037 | 1 | -.042(*) | -.792(**) | -.612(**) | .279(**) | .390(**) | -.151(**) | .071(**) | -0.016 | .067(**) | .411(**) | .290(**) | .040(*) | -0.025 | .284(**) | .251(**) | -.080(**) | 0 | -.156(**) | -0.014 |
| LOAN_ COV | -.211(**) | -.116(**) | -.109(**) | -.042(*) | 1 | .111(**) | -0.035 | -.148(**) | -.081(**) | -0.019 | .086(**) | .175(**) | .122(**) | -0.011 | 0.037 | 0.017 | 0.008 | 0.021 | 0.036 | .060(**) | .076(**) | .086(**) | .071(**) |
| LIQ | .045(*) | .059(**) | -.099(**) | -.792(**) | .111(**) | 1 | .418(**) | -.314(**) | -.308(**) | 0.035 | -.083(**) | 0.035 | -0.031 | -.286(**) | -.163(**) | -.167(**) | -.093(**) | -.167(**) | -.281(**) | .070(**) | -0.009 | .152(**) | -0.005 |
| RES_ CAP | .266(**) | -0.036 | .552(**) | -.612(**) | -0.035 | .418(**) | 1 | -0.036 | -.238(**) | .268(**) | -.078(**) | -0.044 | -.193(**) | -.318(**) | -.269(**) | -.100(**) | -.059(**) | -.257(**) | -.306(**) | .067(**) | .040(*) | .066(**) | .066(**) |
| OPE_EFF | -.068(**) | -.237(**) | .152(**) | .279(**) | -.148(**) | -.314(**) | -0.036 | 1 | .569(**) | .067(**) | 0.022 | -0.041 | -.064(**) | .089(**) | .084(**) | -0.022 | -0.021 | .078(**) | .042(*) | -0.022 | -0.008 | -0.024 | -0.001 |
| INC_CAP | -.132(**) | -.114(**) | 0.018 | .390(**) | -.081(**) | -.308(**) | -.238(**) | .569(**) | 1 | -.265(**) | 0.011 | -.091(**) | -0.021 | .502(**) | .512(**) | 0.027 | -.048(*) | .355(**) | .285(**) | -.077(**) | -0.012 | -.152(**) | -0.02 |
| LAB_ COST | 0.021 | -.297(**) | .216(**) | -.151(**) | -0.019 | 0.035 | .268(**) | .067(**) | -.265(**) | 1 | -0.021 | 0.021 | -.084(**) | -.419(**) | -.337(**) | -0.02 | 0.029 | -.182(**) | -.138(**) | .076(**) | 0.002 | .174(**) | 0.024 |
| MEM_ GRO | -.197(**) | -.137(**) | -.062(**) | .071(**) | .086(**) | -.083(**) | -.078(**) | 0.022 | 0.011 | -0.021 | 1 | .196(**) | .617(**) | -0.011 | 0 | 0.042 | .196(**) | -.140(**) | 0.011 | -0.013 | -0.019 | 0.036 | -0.013 |
| LOAN_ GRO | -.247(**) | -.170(**) | -.084(**) | -0.016 | .175(**) | 0.035 | -0.044 | -0.041 | -.091(**) | 0.021 | .196(**) | 1 | .349(**) | -.155(**) | -.096(**) | -0.013 | .142(**) | -.165(**) | -.093(**) | 0.043 | 0.003 | .092(**) | 0.009 |
| SHARE_ GRO | -.363(**) | -.161(**) | -.227(**) | .067(**) | .122(**) | -0.031 | -.193(**) | -.064(**) | -0.021 | -.084(**) | .617(**) | .349(**) | 1 | 0.029 | -0.008 | .053(*) | .153(**) | -.054(*) | .072(**) | .051(*) | -0.003 | .096(**) | 0.002 |
| STO_RET | -.093(**) | .131(**) | -.108(**) | .411(**) | -0.011 | -.286(**) | -.318(**) | .089(**) | .502(**) | -.419(**) | -0.011 | -.155(**) | 0.029 | 1 | .572(**) | .095(**) | -.066(**) | .629(**) | .540(**) | -.101(**) | -0.009 | -.251(**) | -0.029 |
| ROA | -.090(**) | 0.036 | -.071(**) | .290(**) | 0.037 | -.163(**) | -.269(**) | .084(**) | .512(**) | -.337(**) | 0 | -.096(**) | -0.008 | .572(**) | 1 | .048(*) | -.046(*) | .388(**) | .323(**) | -.080(**) | -0.01 | -.172(**) | -0.025 |
| M1b | -.054(**) | -0.007 | -.109(**) | .040(*) | 0.017 | -.167(**) | -.100(**) | -0.022 | 0.027 | -0.02 | 0.042 | -0.013 | .053(*) | .095(**) | .048(*) | 1 | .158(**) | -.187(**) | .506(**) | -0.022 | -0.001 | -0.019 | -0.005 |
| GDP | -0.017 | 0.003 | -.079(**) | -0.025 | 0.008 | -.093(**) | -.059(**) | -0.021 | -.048(*) | 0.029 | .196(**) | .142(**) | .153(**) | -.066(**) | -.046(*) | .158(**) | 1 | -.311(**) | .258(**) | -0.036 | -0.002 | -0.023 | -0.005 |
| RATE | -.133(**) | -.038(*) | -.219(**) | .284(**) | 0.021 | -.167(**) | -.257(**) | .078(**) | .355(**) | -.182(**) | -.140(**) | -.165(**) | -.054(*) | .629(**) | .388(**) | -.187(**) | -.311(**) | 1 | .595(**) | -0.006 | 0 | -.080(**) | -0.009 |
| RATE_ SPR | -.153(**) | -0.036 | -.291(**) | .251(**) | 0.036 | -.281(**) | -.306(**) | .042(*) | .285(**) | -.138(**) | 0.011 | -.093(**) | .072(**) | .540(**) | .323(**) | .506(**) | .258(**) | .595(**) | 1 | -0.034 | -0.002 | -.087(**) | -0.012 |
| π_ merton | -.146(**) | -.193(**) | .043(*) | -.080(**) | .060(**) | .070(**) | .067(**) | -0.022 | -.077(**) | .076(**) | -0.013 | 0.043 | .051(*) | -.101(**) | -.080(**) | -0.022 | -0.036 | -0.006 | -0.034 | 1 | .418(**) | .851(**) | .467(**) |
| π_ shumway | 0.014 | -0.036 | .073(**) | 0 | .076(**) | -0.009 | .040(*) | -0.008 | -0.012 | 0.002 | -0.019 | 0.003 | -0.003 | -0.009 | -0.01 | -0.001 | -0.002 | 0 | -0.002 | .418(**) | 1 | .371(**) | .994(**) |
| σv_ merton | -.231(**) | -.319(**) | -.075(**) | -.156(**) | .086(**) | .152(**) | .066(**) | -0.024 | -.152(**) | .174(**) | 0.036 | .092(**) | .096(**) | -.251(**) | -.172(**) | -0.019 | -0.023 | -.080(**) | -.087(**) | .851(**) | .371(**) | 1 | .439(**) |
| σv_ shumway | 0.006 | -.068(**) | .097(**) | -0.014 | .071(**) | -0.005 | .066(**) | -0.001 | -0.02 | 0.024 | -0.013 | 0.009 | 0.002 | -0.029 | -0.025 | -0.005 | -0.005 | -0.009 | -0.012 | .467(**) | .994(**) | .439(**) | 1 |

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table 3 Summary Statistics:Non-time-varying covariates from CULROC

| | All sample credit unions | Distress credit unions |
|---|---|---|
| Distribution by region_type | | |
| West | 0.813 | 0.817 |
| East | 0.187 | 0.183 |
| | | |
| Distribution by common bond | | |
| Single | 0.164 | 0.172 |
| Multiple | 0.836 | 0.828 |
| | | |
| Distribution by year of formation | | |
| | | |
| 1961-1970 | 0.088 | 0.072 |
| 1971-1980 | 0.499 | 0.453 |
| 1981-1990 | 0.212 | 0.183 |
| 1991-2000 | 0.144 | 0.283 |
| 2001- | 0.057 | 0.009 |

Table 4 Mean values of time-varying covariates by observation: All sample credit unions from CULROC

| | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 |
|---|---|---|---|---|---|---|---|---|---|
| number | 307 | 308 | 308 | 310 | 310 | 311 | 313 | 314 | 314 |
| LASSET | 3.6300 | 3.6500 | 3.6700 | 3.7000 | 3.7200 | 3.7300 | 3.7400 | 3.7400 | 3.7500 |
| CAP_ADE | 0.0708 | 0.0716 | 0.0776 | 0.0815 | 0.0848 | 0.0887 | 0.0923 | 0.1005 | 0.1030 |
| LOAN_RATIO | 0.6403 | 0.6045 | 0.5591 | 0.5170 | 0.4978 | 0.5020 | 0.4976 | 0.4888 | 0.4573 |
| LOAN_COV | 5.9400 | 7.5700 | 7.7000 | 4.9500 | 6.9700 | 5.5800 | 4.9500 | 5.1200 | 4.9500 |
| LIQ | 0.2367 | 0.2553 | 0.2521 | 0.2661 | 0.2822 | 0.3133 | 0.3302 | 0.3540 | 0.4062 |
| RES_CAP | 0.1143 | 0.1209 | 0.1420 | 0.1669 | 0.1897 | 0.1940 | 0.2019 | 0.2216 | 0.2488 |
| OPE_EFF | 0.0292 | 0.0310 | 0.0275 | 0.0267 | 0.0279 | 0.0265 | 0.0262 | 0.0277 | 0.0274 |
| INC_CAP | 0.0732 | 0.0678 | 0.0538 | 0.0485 | 0.0485 | 0.0469 | 0.0455 | 0.0458 | 0.0396 |
| LAB_COST | 0.1123 | 0.1224 | 0.1467 | 0.1546 | 0.1518 | 0.1579 | 0.1533 | 0.1499 | 0.1725 |
| MEM_GRO | 0.0080 | 0.0103 | 0.0261 | 0.0249 | 0.0205 | 0.0140 | 0.0071 | 0.0048 | 0.0050 |
| LOAN_GRO | -0.0095 | -0.0193 | -0.0412 | -0.0434 | 0.0106 | 0.0671 | 0.0157 | 0.0044 | -0.0512 |
| SHARE_GRO | 0.0277 | 0.0288 | 0.0358 | 0.0420 | 0.0393 | 0.0162 | 0.0115 | 0.0079 | 0.0131 |
| STO_RET | 0.0388 | 0.0323 | 0.0238 | 0.0192 | 0.0181 | 0.0169 | 0.0170 | 0.0151 | 0.0103 |
| ROA | 0.0459 | 0.0376 | 0.0264 | 0.0221 | 0.0208 | 0.0210 | 0.0199 | 0.0181 | 0.0120 |
| M1b | 0.1058 | -0.0102 | 0.1701 | 0.1183 | 0.1898 | 0.0710 | 0.0530 | 0.0644 | -0.0294 |
| GDP | -0.0249 | 0.0487 | 0.0267 | 0.0638 | 0.0324 | 0.0432 | 0.0541 | -0.0135 | -0.0147 |
| RATE | 0.0462 | 0.0409 | 0.0238 | 0.0147 | 0.0111 | 0.0122 | 0.0140 | 0.0153 | 0.0171 |
| RATE_SPR | 0.0299 | 0.0290 | 0.0315 | 0.0263 | 0.0255 | 0.0245 | 0.0209 | 0.0183 | -0.0176 |
| π_merton | 0.0888 | 0.0823 | 0.0819 | 0.0817 | 0.0835 | 0.0843 | 0.0831 | 0.1042 | 0.1046 |
| π_shumway | 0.1391 | 0.1394 | 0.1574 | 0.1668 | 0.1718 | 0.1724 | 0.1689 | 0.1919 | 0.1950 |
| σv_merton | 0.3395 | 0.3386 | 0.3386 | 0.3377 | 0.3385 | 0.3378 | 0.3359 | 0.3543 | 0.3543 |
| σv_shumway | 0.2714 | 0.2750 | 0.2828 | 0.2861 | 0.2895 | 0.2929 | 0.2926 | 0.3151 | 0.3146 |
| π_α_up | 0.4230 | 0.4288 | 0.4405 | 0.4464 | 0.4490 | 0.4502 | 0.4459 | 0.4568 | 0.4589 |
| π_α_down | 0.1150 | 0.1136 | 0.1293 | 0.1372 | 0.1418 | 0.1426 | 0.1400 | 0.1631 | 0.1659 |
| π_β_up | 0.4614 | 0.4671 | 0.4915 | 0.5040 | 0.5102 | 0.5119 | 0.5040 | 0.5469 | 0.5471 |
| π_β_down | 0.0653 | 0.0676 | 0.0789 | 0.0850 | 0.0892 | 0.0876 | 0.0862 | 0.1017 | 0.1053 |
| Distress_rate | 0.0325 | 0.0357 | 0.0747 | 0.1226 | 0.1742 | 0.1576 | 0.1438 | 0.1592 | 0.1688 |

Note：It takes the π_shumway according to the setting value of term structure and equity volatility, and develops four simplified probabilities. Those simplified probabilities define π(term structure volatility, equity volatility), such as π_α_up (0.5,0.25)、π_α_down (0.005,0.25)、π_β_up (0.05,2.5)、π_β_down (0.05,0.025).

Table 5 Mean values of time-varying covariates by observation: Sample credit unions that distressed and don¡t distressed during the subsequent one-year period from CULROC

| | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 |
|---|---|---|---|---|---|---|---|---|---|
| No distress num | 297 | 297 | 285 | 272 | 256 | 262 | 268 | 264 | 261 |
| LASSET | 3.6400 | 3.6800 | 3.7300 | 3.7600 | 3.8000 | 3.8200 | 3.8100 | 3.8200 | 3.8600 |
| CAP_ADE | 0.0707 | 0.0714 | 0.0771 | 0.0808 | 0.0835 | 0.0872 | 0.0905 | 0.0981 | 0.0991 |
| LOAN_RATIO | 0.6399 | 0.6028 | 0.5647 | 0.5337 | 0.5147 | 0.5152 | 0.5045 | 0.4985 | 0.4567 |
| LOAN_COV | 5.7900 | 7.5100 | 8.1800 | 4.8200 | 7.4900 | 6.1200 | 5.6600 | 5.5500 | 5.5000 |
| LIQ | 0.2418 | 0.2616 | 0.2542 | 0.2633 | 0.2778 | 0.3098 | 0.3310 | 0.3546 | 0.4158 |
| RES_CAP | 0.1127 | 0.1212 | 0.1379 | 0.1560 | 0.1699 | 0.1773 | 0.1921 | 0.2080 | 0.2340 |
| OPE_EFF | 0.0295 | 0.0313 | 0.0275 | 0.0266 | 0.0273 | 0.0265 | 0.0257 | 0.0272 | 0.0257 |
| INC_CAP | 0.0744 | 0.0693 | 0.0554 | 0.0506 | 0.0507 | 0.0493 | 0.0472 | 0.0478 | 0.0411 |
| LAB_COST | 0.1089 | 0.1168 | 0.1367 | 0.1414 | 0.1327 | 0.1421 | 0.1383 | 0.1327 | 0.1505 |
| MEM_GRO | 0.0078 | 0.0117 | 0.0289 | 0.0283 | 0.0220 | 0.0164 | 0.0094 | 0.007 | 0.011 |
| LOAN_GRO | -0.0111 | -0.0166 | -0.0433 | -0.0412 | 0.0198 | 0.0164 | 0.0135 | -0.0043 | -0.0411 |
| SHARE_GRO | 0.0274 | 0.0317 | 0.0380 | 0.0406 | 0.0435 | 0.0211 | 0.0121 | 0.0107 | 0.0195 |
| STO_RET | 0.0395 | 0.0328 | 0.0250 | 0.0208 | 0.0198 | 0.0189 | 0.0186 | 0.0167 | 0.0114 |
| ROA | 0.0470 | 0.0388 | 0.0281 | 0.0244 | 0.0245 | 0.0238 | 0.0222 | 0.0206 | 0.0151 |
| M1b | 0.1058 | -0.0102 | 0.1701 | 0.1183 | 0.1898 | 0.0710 | 0.0530 | 0.0644 | -0.0294 |
| GDP | -0.0249 | 0.0487 | 0.0267 | 0.0638 | 0.0324 | 0.0432 | 0.0541 | -0.0135 | -0.0147 |
| RATE | 0.0462 | 0.0409 | 0.0238 | 0.0147 | 0.0111 | 0.0122 | 0.0140 | 0.0153 | 0.0171 |
| RATE_SPR | 0.0299 | 0.0290 | 0.0315 | 0.0263 | 0.0255 | 0.0245 | 0.0209 | 0.0183 | -0.0176 |
| π _merton | 0.0850 | 0.0812 | 0.0759 | 0.0685 | 0.0740 | 0.0705 | 0.0702 | 0.0967 | 0.0988 |
| π _shumway | 0.1352 | 0.1375 | 0.1473 | 0.1512 | 0.1529 | 0.1562 | 0.1526 | 0.1783 | 0.1874 |
| σ v_merton | 0.3370 | 0.3430 | 0.3237 | 0.3149 | 0.3376 | 0.3142 | 0.1438 | 0.3554 | 0.3568 |
| σ v_shumway | 0.2686 | 0.2754 | 0.2724 | 0.2709 | 0.2771 | 0.2749 | 0.2062 | 0.3023 | 0.3047 |
| π _ α _up | 0.4223 | 0.4293 | 0.4340 | 0.4379 | 0.4384 | 0.4439 | 0.4362 | 0.4523 | 0.4562 |
| π _ α _down | 0.1111 | 0.1119 | 0.1200 | 0.1220 | 0.1249 | 0.1271 | 0.1248 | 0.1503 | 0.1589 |
| π _ β _up | 0.4563 | 0.4639 | 0.4758 | 0.4805 | 0.4793 | 0.4882 | 0.4798 | 0.5260 | 0.5354 |
| π _ β _down | 0.0624 | 0.0664 | 0.0723 | 0.0742 | 0.0784 | 0.0763 | 0.0739 | 0.0927 | 0.0998 |
| Distress Num | 10 | 11 | 23 | 38 | 54 | 49 | 45 | 50 | 53 |
| LASSET | 3.3500 | 2.8800 | 2.9600 | 3.3400 | 3.3500 | 3.2400 | 3.2800 | 3.3100 | 3.2000 |
| CAP_ADE | 0.0759 | 0.0759 | 0.0843 | 0.0862 | 0.0908 | 0.0965 | 0.1031 | 0.1129 | 0.1219 |
| LOAN_RATIO | 0.6531 | 0.6520 | 0.4896 | 0.4051 | 0.4177 | 0.4319 | 0.4570 | 0.4374 | 0.4603 |
| LOAN_COV | 10.390 | 9.2900 | 1.7400 | 5.9500 | 4.4800 | 2.6400 | 0.6950 | 2.9000 | 2.2500 |
| LIQ | 0.0866 | 0.0836 | 0.2260 | 0.2863 | 0.3027 | 0.3318 | 0.3252 | 0.3503 | 0.3585 |
| RES_CAP | 0.1613 | 0.1138 | 0.1925 | 0.2383 | 0.2838 | 0.2830 | 0.2598 | 0.2939 | 0.3212 |
| OPE_EFF | 0.0190 | 0.0229 | 0.0275 | 0.0272 | 0.0308 | 0.0260 | 0.0288 | 0.0304 | 0.0358 |
| INC_CAP | 0.0373 | 0.0284 | 0.0337 | 0.0338 | 0.0382 | 0.0338 | 0.0355 | 0.0353 | 0.0325 |
| LAB_COST | 0.2140 | 0.2752 | 0.2708 | 0.2452 | 0.2427 | 0.2424 | 0.2431 | 0.2407 | 0.2807 |
| MEM_GRO | 0.0159 | -0.0275 | -0.0092 | 0.0012 | 0.0134 | 0.0010 | -0.0072 | -0.0066 | -0.0224 |
| LOAN_GRO | 0.0379 | -0.0930 | -0.0143 | -0.0521 | -0.0332 | 0.0590 | 0.0285 | 0.0502 | -0.1007 |
| SHARE_GRO | 0.0346 | -0.0497 | 0.0078 | 0.0529 | 0.0197 | -0.0105 | 0.0085 | -0.0071 | -0.0185 |
| STO_RET | 0.0166 | 0.0134 | 0.0072 | 0.0086 | 0.0098 | 0.0059 | 0.0077 | 0.0068 | 0.0047 |
| ROA | 0.0045 | 0.0055 | 0.0055 | 0.0057 | 0.0035 | 0.0060 | 0.0062 | 0.0049 | -0.0033 |
| M1b | 0.1058 | -0.0102 | 0.1701 | 0.1183 | 0.1898 | 0.0710 | 0.0530 | 0.0644 | -0.0294 |
| GDP | -0.0249 | 0.0487 | 0.0267 | 0.0638 | 0.0324 | 0.0432 | 0.0541 | -0.0135 | -0.0147 |
| RATE | 0.0462 | 0.0409 | 0.0238 | 0.0147 | 0.0111 | 0.0122 | 0.0140 | 0.0153 | 0.0171 |
| RATE_SPR | 0.0299 | 0.0290 | 0.0315 | 0.0263 | 0.0255 | 0.0245 | 0.0209 | 0.0183 | -0.0176 |
| π _merton | 0.2015 | 0.1116 | 0.1566 | 0.1775 | 0.1287 | 0.1575 | 0.1603 | 0.1437 | 0.1332 |
| π _shumway | 0.2542 | 0.1892 | 0.2832 | 0.2778 | 0.2609 | 0.2591 | 0.2660 | 0.2636 | 0.2322 |
| σ v_merton | 0.4142 | 0.2191 | 0.5236 | 0.5067 | 0.3432 | 0.4642 | 1.4769 | 0.3482 | 0.3420 |
| σ v_shumway | 0.3551 | 0.2637 | 0.4107 | 0.3961 | 0.3486 | 0.3887 | 0.8067 | 0.3828 | 0.3633 |
| π _ α _up | 0.4450 | 0.4136 | 0.5204 | 0.5066 | 0.4991 | 0.4835 | 0.5034 | 0.4808 | 0.4721 |
| π _ α _down | 0.2302 | 0.1568 | 0.2441 | 0.2437 | 0.2221 | 0.2250 | 0.2309 | 0.2308 | 0.2001 |
| π _ β _up | 0.6121 | 0.5518 | 0.6852 | 0.6703 | 0.6565 | 0.6384 | 0.6483 | 0.6575 | 0.6050 |
| π _ β _down | 0.1525 | 0.0990 | 0.1599 | 0.1617 | 0.1402 | 0.1479 | 0.1594 | 0.1492 | 0.1321 |

Note：It takes the π_shumway according to the setting value of term structure and equity volatility, and develops four simplified probabilities. Those simplified probabilities define π(term structure volatility, equity volatility), such as π_α_up (0.5,0.25)、π_α_down (0.005,0.25)、π_β_up (0.05,2.5)、π_β_down (0.05,0.025).

Table 6 Hazard function estimation results

| Equation | I | II | III | IV | V | VI | VII | VIII |
|---|---|---|---|---|---|---|---|---|
| Sample | 01~03 | 04~06 | 07~09 | All | EAST | WEST | Single | MUT |
| $\pi$ _merton | 0.043 | -8.522 | 0.712 | -1.424 | -5.408 | -2.146** | -5.527 | -0.274 |
| | (0.07) | (-0.90) | (0.15) | (-1.48) | (-0.90) | (-2.18) | (-1.50) | (-0.26) |
| $\pi$ _shumway | -0.411 | 5.286 | 28.338* | 5.276 | 16.165 | 1.154 | -1.703 | 5.830 |
| | (-0.12) | (0.49) | (1.87) | (1.19) | (1.14) | (0.25) | (-0.18) | (1.14) |
| $\sigma$ v_merton | | | | -0.449 | 4.297 | -0.575** | -0.569 | 0.080 |
| | | | | (-1.54) | (1.24) | (-1.98) | (-0.55) | (0.07) |
| $\sigma$ v_shumway | -0.459 | -0.397 | 1.922 | 1.785** | -18.14** | 2.264*** | 1.352 | 0.209 |
| | (-0.54) | (-0.25) | (1.87) | (2.21) | (-2.71) | (2.79) | (0.66) | (0.53) |
| $\pi$ _ $\alpha$ _up | -0.796 | -3.812 | -3.339 | -3.454** | -15.76*** | -3.361** | -7.712 | -4.729*** |
| | (-1.06) | (-0.64) | (-0.50) | (-2.45) | (-3.23) | (-2.26) | (-1.59) | (-3.16) |
| $\pi$ _ $\alpha$ _down | -1.334 | 0.593 | -13.201 | -3.191 | -30.98* | 0.892 | 11.072 | -3.835 |
| | (-0.39) | (0.05) | (-0.79) | (-0.74) | (-1.71) | (0.20) | (1.14) | (-0.77) |
| $\pi$ _ $\beta$ _up | 0.778 | 1.049 | -1.756 | 0.737 | 7.695* | 1.863* | 1.060 | 1.375 |
| | (0.91) | (0.22) | (0.56) | (0.71) | (1.92) | (1.69) | (0.35) | (1.21) |
| $\pi$ _ $\beta$ _down | 7.222*** | 1.873 | -17.406 | 3.214* | 49.11*** | 2.145 | 1.307 | 2.694 |
| | (3.52) | (0.76) | (-0.75) | (1.70) | (2.95) | (1.14) | (0.19) | (1.26) |
| LAGE | -0.51 | 1.426 | 5.078*** | 0.870** | 0.954 | 1.269** | 0.189 | 1.502*** |
| | (-1.20) | (0.92) | (3.06) | (2.35) | (1.33) | (2.54) | (0.29) | (3.25) |
| LASSET | 0.132 | -1.646 | -14.078*** | -1.514*** | -3.172*** | -1.287*** | -0.413 | -2.892*** |
| | (1.31) | (-1.35) | (-6.46) | (-6.52) | (-3.55) | (-5.31) | (-1.14) | (-8.84) |
| CAP_ADE | 0.506 | -5.078 | 5.098 | -7.97** | -14.204 | -5.956* | -0.572 | -15.036*** |
| | (0.19) | (-0.59) | (0.39) | (-2.46) | (-1.62) | (-1.68) | (-0.07) | (-4.06) |
| LOAN_RATIO | 0.406 | -1.975 | -6.371** | -0.542 | -2.590 | -0.483 | -0.633 | -0.250 |
| | (1.04) | (-1.07) | (-2.36) | (-0.84) | (-1.13) | (-0.70) | (-0.415) | (-0.34) |
| LOAN_COV | -0.001 | -0.0045 | 0.0026 | -0.0002 | 0.0015 | -0.0004 | -0.0026 | -0.0007 |
| | (-0.78) | (-1.14) | (0.32) | (-0.13) | (0.22) | (-0.19) | (-0.79) | (-0.24) |
| LIQ | -0.617** | -1.270 | -2.275 | -1.393*** | -2.163 | -1.226** | -1.111 | -1.299** |
| | (-2.35) | (-1.06) | (-1.16) | (-2.74) | (-1.29) | (-2.29) | (-0.97) | (-2.28) |
| RES_CAP | -0.115 | 1.792 | -2.675 | 1.990*** | 0.707 | 1.985*** | 2.907* | 1.496** |
| | (-0.18) | (1.59) | (-1.29) | (3.55) | (0.19) | (3.50) | (1.71) | (2.48) |
| OPE_EFF | -1.175 | -1.520 | -14.327 | 8.718** | 0.676 | 8.072* | 50.877*** | 7.567** |
| | (-0.83) | (-0.11) | (-1.12) | (2.53) | (0.12) | (1.72) | (3.15) | (2.12) |
| INC_CAP | 0.322 | -8.869 | 3.470 | -2.239 | 3.170 | -2.210 | -48.004*** | -0.290 |
| | (0.47) | (-1.02) | (0.30) | (-1.14) | (0.32) | (-1.05) | (-3.62) | (-0.15) |
| LAB_COST | 1.180*** | 3.329*** | 13.182*** | 7.312*** | 14.235*** | 5.873*** | 2.248 | 7.892*** |
| | (2.76) | (3.02) | (5.33) | (11.53) | (6.29) | (8.77) | (1.63) | (10.88) |
| MEM_GRO | 0.085 | 1.497 | -3.324 | -0.523 | -0.588 | -0.514 | -2.2696* | 0.114 |
| | (0.34) | (1.26) | (-1.31) | (-0.87) | (-0.39) | (-0.78) | (-1.89) | (0.16) |
| LOAN_GRO | 0.029 | 0.713* | -0.087 | 0.216 | 0.544 | 0.249* | 0.159 | 0.072 |
| | (0.18) | (1.79) | (-0.16) | (1.51) | (0.76) | (1.70) | (0.88) | (0.30) |
| SHARE_GRO | -0.614** | 0.370 | 7.236*** | 1.112** | 1.094 | 1.310** | 1.496* | 1.075 |
| | (-2.00) | (0.41) | (3.18) | (2.10) | (0.74) | (2.26) | (1.74) | (1.53) |
| ROA | 0.420 | -21.892*** | -32.769*** | -9.802*** | -6.692 | -8.193*** | -2.245 | -14.012*** |
| | (0.49) | (-4.25) | (-3.10) | (-4.97) | (-1.34) | (-3.70) | (-0.50) | (-6.22) |
| M1b | 0.906** | -1.741 | 3.489 | 0.313 | -1.756 | 1.177 | -4.073 | 1.272 |
| | (2.51) | (1.25) | (1.55) | (0.30) | (-0.68) | (1.01) | (-1.53) | (1.11) |
| GDP | 2.365** | -12.656* | -2.316 | -1.599 | -6.502 | 0.062 | -9.384** | -0.099 |
| | (2.54) | (-1.77) | (-0.74) | (-0.85) | (-1.42) | (0.03) | (-2.03) | (-0.05) |
| RATE | | | | 5.464 | -9.992 | 12.754 | -10.608 | 5.571 |
| | | | | (0.62) | (-0.46) | (1.28) | (-0.47) | (0.57) |
| RATE_SPR | | | | -68.56*** | -34.799 | -71.190*** | 56.11 | -104.52*** |
| | | | | (-3.04) | (-0.62) | (-2.90) | (1.03) | (-4.24) |
| Observations | 922 | 929 | 941 | 2792 | 520 | 2272 | 457 | 2335 |
| Credit unions | 308 | 311 | 314 | 314 | 58 | 256 | 53 | 261 |
| distress | 44 | 141 | 148 | 333 | 61 | 272 | 57 | 276 |
| Adjusted R-squared | 0.2411 | 0.4874 | 0.5145 | 0.3688 | 0.4177 | 0.3683 | 0.425 | 0.3756 |

Note: A positive coef cient on a particular variable implies that the hazard rate is increasing in that variable, or that the expected time to default is decreasing in that variable. Standard errors are in parentheses (*** Estimated coefficient significantly different from zero, two-tail test, 1% significance level. ** As above, 5% significance level. * As above, 10% significance level.

Table 7 Models estimation results and Forecasts

| Models | I | II | III | IV | V | VI | VII | VIII |
|---|---|---|---|---|---|---|---|---|
| Methods | Merton | Shumway | Merton& Shumway | Hazard& Merton | Hazard | Hazard& Shumway | Hazard& EDF | Logit |
| $\pi$ _merton | 1.264*** | | -4.689*** | 0.907 | | | -1.424 | -10.592* |
| | (4.19) | | (-4.89) | (1.42) | | | (-1.48) | (-1.91) |
| $\pi$ _shumway | | 14.596*** | 5.721 | | | 7.844* | 5.276 | 17.310 |
| | | (3.29) | (1.19) | | | (1.88) | (1.19) | (1.08) |
| $\sigma$ v_merton | | | | 0.098 | | | -0.449 | 1.301 |
| | | | | (0.49) | | | (-1.54) | (2.21) |
| $\sigma$ v_shumway | | | | | | 0.683 | 1.785** | -4.110 |
| | | | | | | (1.26) | (2.21) | (-1.45) |
| $\pi$ _ $\alpha$ _up | | -5.056*** | -4.734*** | | | -3.581** | -3.454** | -5.281 |
| | | (-3.42) | (-3.21) | | | (-2.54) | (-2.45) | (-1.170) |
| $\pi$ _ $\alpha$ _down | | -12.877*** | -2.391 | | | -6.370 | -3.191 | -38.903** |
| | | (-3.12) | (-0.52) | | | (-1.64) | (-0.74) | (-2.01) |
| $\pi$ _ $\beta$ _up | | 1.752* | 2.729** | | | 0.645 | 0.737 | 4.193 |
| | | (1.67) | (2.56) | | | (0.643) | (0.71) | (1.43) |
| $\pi$ _ $\beta$ _down | | 8.547*** | 9.836*** | | | 3.182* | 3.214* | 48.048* |
| | | (4.56) | (5.22) | | | (1.70) | (1.70) | (1.89) |
| LAGE | | | | 0.919** | 0.894** | 0.904** | 0.870** | -0.035 |
| | | | | (2.48) | (2.42) | (2.44) | (2.35) | (-0.07) |
| LASSET | | | | -1.485*** | -1.522*** | -1.511*** | -1.514*** | -0.301 |
| | | | | (-6.43) | (-6.61) | (-6.52) | (-6.52) | (-1.20) |
| CAP_ADE | | | | -5.61* | -9.330*** | -6.517** | -7.97** | -11.140 |
| | | | | (-1.93) | (-3.11) | (-2.10) | (-2.46) | (-1.34) |
| LOAN_RATIO | | | | -0.531 | -0.676 | -0.449 | -0.542 | -4.091* |
| | | | | (-0.82) | (-1.04) | (-0.70) | (-0.84) | (-1.81) |
| LOAN_COV | | | | 0.00008 | 0.0003 | -0.0002 | -0.0002 | -0.012 |
| | | | | (0.036) | (0.135) | (-0.10) | (-0.13) | (-1.17) |
| LIQ | | | | -1.258** | -1.320*** | -1.364*** | -1.393*** | -4.115* |
| | | | | (-2.47) | (-2.60) | (-2.68) | (-2.74) | (-1.91) |
| RES_CAP | | | | 2.287*** | 1.968*** | 2.151*** | 1.990*** | 1.476 |
| | | | | (4.13) | (3.53) | (3.89) | (3.55) | (0.67) |
| OPE_EFF | | | | 9.651*** | 9.667*** | 8.622** | 8.718** | 68.235*** |
| | | | | (2.81) | (2.82) | (2.51) | (2.53) | (3.19) |
| INC_CAP | | | | -2.765 | -2.648 | -2.255 | -2.239 | -183.24*** |
| | | | | (-1.41) | (-1.35) | (-1.15) | (-1.14) | (-10.57) |
| LAB_COST | | | | 7.472*** | 7.420*** | 7.361*** | 7.312*** | 6.614*** |
| | | | | (11.77) | (11.73) | (11.60) | (11.53) | (2.63) |
| MEM_GRO | | | | -0.661 | -0.589 | -0.580 | -0.523 | -6.512** |
| | | | | (-1.09) | (-0.98) | (-0.97) | (-0.87) | (-2.35) |
| LOAN_GRO | | | | 0.249* | 0.223 | 0.236* | 0.216 | 0.843 |
| | | | | (1.73) | (1.56) | (1.66) | (1.51) | (0.58) |
| SHARE_GRO | | | | 1.164** | 1.126** | 1.111** | 1.112** | -4.066** |
| | | | | (2.19) | (2.12) | (2.09) | (2.10) | (-2.35) |
| ROA | | | | -10.044*** | -10.167*** | -9.789*** | -9.802*** | |
| | | | | (-5.09) | (-5.17) | (-4.97) | (-4.97) | |
| M1b | | | | 0.347 | 0.259 | 0.365 | 0.313 | 1.338 |
| | | | | (0.33) | (0.24) | (0.35) | (0.30) | (0.23) |
| GDP | | | | -1.843 | -2.138 | -1.427 | -1.599 | -17.723 |
| | | | | (-0.98) | (-1.15) | (-0.76) | (-0.85) | (-1.61) |
| RATE | | | | 3.500 | 2.709 | 5.482 | 5.464 | -78.813 |
| | | | | (0.39) | (0.31) | (0.62) | (0.62) | (-1.63) |
| RATE_SPR | | | | -65.84*** | -69.46*** | -66.89** | -68.56*** | -134.33 |
| | | | | (-2.91) | (-3.08) | (-2.96) | (-3.04) | (-1.02) |
| Observations | 2793 | 2793 | 2973 | 2792 | 2792 | 2792 | 2792 | 1396 |
| Hausman test | 1.82(0.17) | 62.33(0.00) | 67.84(0.00) | 72.7(0.00) | 82.76(0.00) | 87.46(0.00) | 89.40(0.00) | - |
| Adjusted R-squared | 0.0059 | 0.2459 | 0.2528 | 0.3617 | 0.3660 | 0.3677 | 0.3688 | 0.3510 |
| RMSE(1) | 2.7551 | 2.5463 | 2.5377 | 2.2601 | 2.2571 | 2.2502 | 2.2502 | - |

Note: A positive coef cient on a particular variable implies that the hazard rate is increasing in that variable, or that the expected time to default is decreasing in that variable. Standard errors are in parentheses (*** Estimated coefficient significantly different from zero, two-tail test, 1% significance level. ** As above, 5% significance level. * As above, 10% significance level.

Note 1：RMSE(Root Mean Squared Error)：the method of calculating forecast accuracy. The time period chosen to conduct out-of-sample forecasts is between 2008 and 2009, comparing the actual and expected value of each model and further assesses their predictive capability.