

Credit Risk Measurement System

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Abstract

This paper critically reviews the evolution of credit risk measurement on individual loan and loan portfolios of banks and financial institutions. The first generation based on stand-alone unit of expert system is ease of use but tends to be bias and pessimistic on the borrowers. The second development is based on key accounting ratios derived from financial statements of potential borrowers but fail to incorporate market values. Further, the theoretical based model provides reliable measures of credit risk. Recent development measures credit concentration risk at portfolio level which allows financial institutions to assess their risk-taking capacity more effectively.

Keywords: Banks, Credit risk measurement, Default, Financial institutions

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ระบบการวัดความเสี่ยงด้านสินเชื่อ

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บทคัดย่อ

บทความนี้ทบทวนวิวัฒนาการของการวัดความเสี่ยงด้านเครดิตของสินเชื่อและพอร์ตสินเชื่อของธนาคารและสถาบันการเงิน วิวัฒนาการแรกเริ่มจะเป็นระบบการประเมินจากความเห็นของผู้เชี่ยวชาญซึ่งง่ายในการใช้งาน แต่มีแนวโน้มที่จะอคติในแง่ลบกับผู้กู้ ต่อมาจึงได้มีการวิเคราะห์โดยใช้อัตราส่วนทางบัญชีที่สำคัญจากงบการเงินของผู้กู้ แต่ยังมีจุดด้อยที่ไม่ได้คำนึงถึงมูลค่าตามตลาด จากนั้น จึงมีการพัฒนาแบบจำลองเชิงทฤษฎีซึ่งให้มาตรวัดความเสี่ยงด้านเครดิตที่น่าเชื่อถือ โดยวิวัฒนาการล่าสุดของการวัดความเสี่ยงด้านเครดิตได้ให้ความสนใจกับความเสี่ยงด้านการกระจุกตัวของการให้สินเชื่อในระดับพอร์ตโฟลิโอ ซึ่งช่วยให้สถาบันการเงินประเมินความสามารถในการรับความเสี่ยงได้อย่างมีประสิทธิภาพมากขึ้น

คำสำคัญ : ธนาคาร; การวัดความเสี่ยงด้านสินเชื่อ; การผิณฑ์ชำระหนี้; สถาบันการเงิน

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1. Introduction

The primary risk of financial institutions has been credit risk arising through lending. Credit risk is realized whenever borrowers cannot or will not repay their loans on the original terms. Credit risk is one of three separate interrelated risks that financial institutions encounter, specifically, interest rate risk, liquidity risk, and credit risk.

Interest in and concern with credit risk management has been clearly escalated among lending institutions, primarily commercial banks. These financial institutions have reached a certain maturation stage whereby they no longer simply want to make loans easily as before. The default rate is currently thriving, many companies fail to meet their obligation to pay back the loan in time and need a refinancing of some sorts or require renegotiations.

To manage credit risk effectively, financial institutions need to stimulate the congruent sophisticated development of credit risk measurement techniques. The appropriate measurement of credit risks is vitally important to both loan market, and gradually more, derivatives market. Market participants need to know how to measure credit risk in order to be properly compensated for bearing the risk. They also need to know how to evaluate the usefulness of mechanisms to reduce credit risk, such as using collateral or transacting with specialized derivative product companies.

The rest of the paper is organized as follows. The next section provides literature reviews on the development, evolution of the credit risk measurement, and discussion of advantages and disadvantages of each stage of development in credit risk measurement system. The credit

risk measurement at portfolio level is discussed in section 3. Then, the last section provides the conclusion.

2. The Evolution of Credit Risk Measurement System

The development and evolution of the credit risk measurement has been evolved considerably for more than twenty years. Much of traditional credit risk management is passive. Such activity has included transaction limits determined by the customer's credit rating, the transaction's tenor, and the overall exposure level. At this time, there are more active management techniques. These include regular credit reviews, collateral agreements, downgrade triggers, termination clauses, and credit derivatives.

The groundwork for any comprehensive treatment of loans is the initial assessment of the risk for each loan. The advancement of the credit risk measurement has been progressed significantly, which can be grouped into four generations according to the nature and system of the credit risk evaluation process. The credit risk can be analyzed either on a stand-alone basis or portfolio level. The first three group of credit risk assessment; namely the expert system, accounting based system, and theoretical based system, can be referred to as a stand-alone credit risk measurement for individual customers or borrowers, while the latest generation of measuring credit risk, the credit concentration risk system, is analyzed at a portfolio level.

2.1 The first wave: expert system and subjective analysis

The assessment of credit risk in early stage relied exclusively on subjective analysis or the banker's expertise and judgment based on

borrowers' characteristics. These characteristics are known as the five "Cs", namely character, capacity, capital, collateral, and conditions.¹ This traditional system based on banker's subjective rating tends to be biased and pessimistic about the credit risk of the borrowers, it cannot meet the increasingly overwhelming intensity of competition in the loan market. Therefore, the financial institutions have moved away towards more objectively oriented systems.

The bank internal rating systems are extended from the U.S. Office of the Comptroller of the Currency (OCC) to assess the adequacy of their loan loss reserves. The loan portfolios are categorized into low and high quality ratings with different risk levels and score. Treacy and Carey (2000) find that small and medium-size firms rely on qualitative factors while large firms use quantitative methods in determining the ratings of loans. Nevertheless, these internal loan-rating systems are for the overall borrower so cannot apply with the bond-rating systems which rate an individual loan. So, the newer models that rely on bond data to value loans are needed.

2.2 The second wave: accounting based credit-scoring system

The second movement of the credit risk assessment of the loan granting relies on key accounting ratios derived from financial statement models to evaluate the quality of a particular borrower. The credit institutions themselves must assess the probability that a borrower will default

¹ This is based on the definition of Sinkey (1983). Since the more well-known one, the four "Cs", namely character, capacity, capitals, and collateral, are defined differently from various viewpoints among academicians and researchers; therefore, representing the concept by the five "Cs" will cover all ideas presented in this paper.

during the following year. This credit-scoring method based on accounting ratios includes univariate and multivariate credit-scoring system.

In univariate accounting based credit-scoring systems, the decision-makers in the banks and financial institutions weigh against several key accounting ratios of potential borrowers with industrial norms. Beaver (1966) is considered the first modern pioneering work to predict financial failure. The rationale behind the model can best be explained within the framework of cash flow to firms. In his model, the firm is viewed as a reservoir of liquid assets, which is supplied by inflows and drained by outflows. The reservoir serves as a safeguard against variations in the flows. The solvency of the firm can be defined in terms of the probability that the reservoir will be exhausted at which point the firm will be unable to pay its obligations as they mature. Using univariate discriminant analysis, he shows that financial ratios can be used to predict corporate failure. While most subsequent researchers have investigated only bankruptcy, Beaver uses a broader definition of failure. His group of failed firms included bankruptcies, bond defaults, overdrawn bank accounts, and firms that omitted preferred dividends.

For each of five years prior to failure, he computes 30 ratios which are selected by popularity, performance in previous studies, and definition of the prediction error in terms of cash flow concept. The results reveal that six ratios are considered as best predictors of financial failure, namely, cash flow to total debt, net income to total assets, current plus long-term liabilities to total assets, working capital to total assets, current ratio, and no-credit interval. Then, he derives a cut-off point for each ratio, such that firms with ratios above the cut-off point were classified as potential non-failures, while those with lower ratios were classified as potential

failures. This framework is the most important contribution. Beaver finds that financial ratios have failure prediction ability for at least five years before failure and suggests that single ratio can predict failure but the degree of accuracy is different. Further, ratios have greater success in predicting non-failure than failure. So, for decision-making purposes, financial ratios should be complemented by frequency distributions and likelihood ratios.

While in Beaver (1966), all ratios are from accounting data, Beaver (1968) investigates the predictive ability of stock market prices. He argues that if sophisticated investors can predict financial failure, a company's stock price should fall long before failure. He conducts a cumulative test to see if the stock market would predict failure before the accounting ratios and find that the stock market prevails by a slight margin.

In conclusion, the univariate accounting based analysis recognizes certain significant generalizations regarding the performance and trends of particular measurements, the adaptation of their results for assessing bankruptcy potential of firms, both theoretically and practically, is questionable. The shortcomings of the univariate analysis lie on the order of importance. In general, ratios measuring profitability, liquidity, and solvency prevailed as most significant indicators but the order of importance is not clear.

In multivariate models, the key accounting variables are combined and weighted to construct either a credit risk score or a probability of default measure. If this score or probability attains a value above a critical point of reference, a loan applicant is either rejected or subjected to increased scrutiny. The methodologies to develop multivariate credit-scoring systems are the linear probability model, logit, probit,

discriminant analysis, and the Loan Pricing Corporation (LPC) model. Of these methods, discriminant analysis is the foremost one followed by the logit analysis while the LPC model seems to be the simplest one.

The pioneer work in multivariate credit-scoring models is Altman (1968) which proposed a multiple discriminant analysis (MDA) as an appropriate statistical technique. MDA is used to classify an observation into one of several a priori groupings dependent upon the observation's individual characteristics. It is used primarily to classify and make predictions in problems where the dependent variable appears in qualitative form, for example, bankrupt or non-bankrupt events. The discriminant function is in the following form:

$$Z = v_1x_1 + v_2x_2 + \dots + v_nx_n \quad (1)$$

where v_1, v_2, \dots, v_n are discriminant coefficients and x_1, x_2, \dots, x_n are independent variables. This model will convert the individual variable values to a single discriminant score called Z score which is exploited to classify the object. By using the MDA, the combinations of the ratios can be analyzed simultaneously in order to eliminate possible ambiguities and misclassifications observed in earlier studies. The MDA technique also has the advantage of considering an entire profile of characteristics general to the related firms, as well as the interaction of these properties. Another advantage of the MDA is the reduction of the space dimensionality, that is, from the number of different independent variables to the number of original a priori group minus 1. If in the analysis, there are only two groups, then this will be transformed into one dimension.

Altman develops a five-variable linear model consisting of working

capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to book value of total debt, and sales to total assets. The empirical results suggest that the bankruptcy prediction model is an accurate forecaster of failure up to two years prior to bankruptcy and that the accuracy diminishes substantially as the lead time increases.

Deakin (1972) develops an alternative to Beaver (1966) and Altman (1968) models. He uses linear multiple discriminant analysis and 14 of Beaver's ratios to find combination of variables with greatest predictive accuracy. Ratio of cash flow to total debt² is an important variable. He concluded that discriminant analysis can be used to predict business failures as far as three years in advance with a fairly high accuracy.

Later, Libby (1975) employs a subset of Deakin's (1972) 14-variable set. Using principal component analysis, he identifies five independent sources of variation within the 14-variable set. Further, the MDA is employed to test for the classification accuracy. The five dimensions are profitability, activity, liquidity, asset balance, and cash position. Regarding the experiments on the loan officers, Libby find that the loan officers' predictive accuracy is superior to random assignment and concludes that the ratio information is utilized correctly by the loan officers. Thus, Libby's study illustrates the usefulness of principal component analysis in reducing the dimensionality of a data set and shows that accounting ratios enable bankers to make highly accurate and reliable predictions of business failures.

² Cash flow is defined as net income plus depreciation, depletion, and amortization. Total debt is total liabilities plus preferred stock.

Deakin (1977) assesses the impact, frequency, and nature of bankruptcy misclassification using his 1972 model as modified by Libby (1975). The purpose of the extension is to provide an indication of the frequency and nature of misclassification of non-failing companies and to compare auditors' opinions with the model's predictive ability. He uses both linear and quadratic MDA and focuses on the concepts of failing and non-failing rather than failed and non-failed to emphasize that a company may enter the failing state and still avoid the failed state.

Further, Edmister (1972) provides the first failure-prediction model for small business. He employs a zero-one regression technique. The relationship between discriminant analysis and regression coefficients is a proportional one in the two-group case, failure and non-failure. He has the arbitrary correlation coefficient cutoff point to avoid the problem of multicollinearity.

The important explanatory power may be excluded from the regression equation. In his approach, all variables are not entered as the raw ratios. They are transformed into qualitative, zero-one variables based upon arbitrary cutoff points. He believes that the transformations can prevent the extreme and can permit level and trend variables to be combined into a single dichotomous variable.

Then, the most sophisticated and up-to-date MDA model of corporate bankruptcy, the ZETA model, is developed by Altman, Haldeman, and Narayanan (1977). They try to construct, analyze, and test a new bankruptcy classification model which considers explicitly recent developments with respect to business failures. A new ZETA model is effective in classifying bankrupt companies up to five years prior to failure on a sample of corporations consisting of manufacturers and retailers. Both

linear and quadratic classification equations are employed. The ZETA model consists of seven variables which are return on assets, stability of earnings, debt service, cumulative profitability, liquidity, capitalization, and size. The results revealed that the ZETA model outperforms alternative bankruptcy classification strategies in terms of expected cost criteria utilizing prior probabilities and explicit cost of error estimates.

Therefore, in the area of discriminant analysis, all of the models contain ratios based on both stocks and flows, and all contain variables that are closely related to corporate earnings. The variables enter the models either linearly or in a quadratic fashion. Earnings or cash flow variables appear in all of the models, debt appears in several. Another important variable is the company's stock price. It is hard to tell which model discriminates best. Nevertheless, the misclassification rates suggest that the best multidimensional models discriminate better than the best single-variable models, but that the best single-variable models outperform some of the multidimensional models.

Of the multidimensional models, the ZETA model of Altman, Haldeman, and Narayanan (1977) is perhaps the most convincing. It has high discriminatory power, is reasonably parsimonious, and includes accounting and stock market data as well as earnings and debt variables. Further, it is being used in practice by over thirty financial institutions. As a result, although it is unlikely to represent the perfect prediction model, it will be used as a benchmark for judging the plausibility of the theories discussed in later sections.

However, the MDA is subjected to certain statistical requirements imposed on the distributional properties of the predictors. The variance-covariance matrices of the predictors should be the same for both groups;

failed and non-failed firms. A requirement of normally distributed predictors certainly mitigates against the use of dummy independent variables. This will limit the scope of the investigation. Further, ratios are treated as completely independent and the extreme data points may be bias. The output of the application of an MDA model is a score which has little intuitive interpretation, since it is basically an ordinal ranking discriminatory device. In the matching procedures, failed and non-failed firms are matched according to arbitrary criteria.

Next, considering another method of multivariate accounting based credit-scoring system, the logit analysis, which is chosen to avoid some problems associated with the MDA. The major advantage is that no assumption regarding prior probabilities of bankruptcy and the distribution of predictors is required. So, it does not suffer from the strict distributional assumption. Further, in the logit analysis, the exogenous variables explicitly determine group membership whereas in the MDA, it is taken as given. However, similar to the discriminant analysis, logit analysis uses a set of accounting variables to predict the probability of borrower default, assuming that the probability of default is logistically distributed. The cumulative probability of default takes a logistic functional form and is constrained to fall between 0 and 1.

he basic equation of the logit model is as follows:

$$\Pr(Y_i = 1) = \frac{1}{1 + e^{-w_i}} \quad ; i = 1, \dots, N \quad (2)$$

where w_i is equal to $b_0 + \sum_{j=1}^M b_j x_{ij}$; Y_i is a dependent variable which represents the final outcome, $Y_i = 1$ for failed banks and $Y_i = 0$ for non-failed banks; N is total number of observations; M is number of explanatory variables; and x_{ij} is value of the j^{th} variable for the i^{th}

observation. The logit model estimates the coefficients in order to produce a set of probability estimates. Then, those observations where failure occurred are assigned high ex ante probabilities of failure while those which did not fail are assigned low probabilities. A good fit is a set of coefficients that comes as closed as possible to this objective.

Martin (1977) applies the logit analysis to the bank early warning problem. He uses both logit and discriminant analysis to predict bank failures. The two approaches are compared by computing classification accuracy for failed and non-failed banks. The empirical results find that both models give similar classifications in terms of identifying failures and non-failures. This is in contrast to Nittayagasetwat (1998) who applied the logit model and multivariate discriminant analysis in the case of Thailand. He finds that MDA has more predictive power and gives higher accuracy than the logit model in predicting the bankruptcy both in the learning and holdout samples. The logit analysis is also employed in Vititayanon, Asawintaragoon, and Klinmali (1996) who use 6 variables which are debt to equity ratio, return on assets, interest coverage ratio, beta, real GDP growth, and dummy variable which is equal to 1 if that company is a financial institution and 0 otherwise. The results show that their 6 variables are significant and this logit model has the ability to predict the credit rating accurately.

Next, the Loan Pricing Corporation (LPC) has developed the LPC Risk Rater™ which is a Windows based software application designed to estimate default probabilities and expected losses for commercial loans with a time horizon up to five years. The LPC Risk Rater™ uses a multivariate, statistically based risk rating model developed from empirical data in LPC's proprietary Loan Loss Database, as well as public data sources.

The Risk Rater™ estimates the default probability of a borrower based upon a series of quantitative variables (borrower financial ratios and market value data) and subjective factors (qualitative borrower characteristics). LPC's research has shown that the combination of these quantitative variables provides optimal statistical significance in estimating the probability of default by a borrower. The Risk Rater™ then estimates the expected loss for a loan by multiplying the estimated default probability by an estimated loss-in-event-of-default (LIED) percentage for the loan. LPC's research has shown LIED to be a function of the loan's primary collateral.

Although the multivariate accounting based credit-scoring models have performed quite well, they are subjected to several criticisms. First, since they base on accounting data, they may fail to pick up those data that would be reflected in capital market data and values. Second, the linear discriminant analysis and the linear probability models may fail to forecast accurately due to the non-linearity. Third, the credit-scoring bankruptcy prediction models are linked to an underlying theoretical model. Therefore, there are new approaches proposed as alternatives to traditional credit-scoring and bankruptcy prediction models.

Bankruptcy theory can serve several useful functions. It can provide logically consistent explanations for the existing empirical successes. Further, theory can organize the search for new empirical models. These new theoretical based models may be especially effective, since by suggesting variables and functional forms, explicit theoretical frameworks reduce the scope for statistical over fitting. Also, the eventual development of theoretical based empirical models should increase users' confidence

that bankruptcy prediction models can be applied effectively to different data sets. Further, because the concepts underlying theoretical based models are explicit, it is usually easier and safer in practical applications to make judgmental modifications of the variables that go into the model.

2.3 The third wave: theoretical based model

As the strictly subjective judgment of conventional style cannot be an adequate base for discriminating among firms' default prospects, the measurement of default probabilities is speedily evolving into a science by using key accounting based ratios, resembling the second generation. The development tends to move forward to a more theoretically based model, which can be classified into the following groups.

2.3.1 Option based model

The most widely used credit-scoring model was not derived from experience with commercial loan defaults but, rather, from experience with defaults in the public bond markets. An alternative only just developed credit-scoring model uses option-pricing theory to relate movements in the price of a borrowing firm's equity to an estimate of the distribution of the market value of the firm's assets. This asset value distribution, in turn, is used to estimate the probability of the firm becoming insolvent. The firm is considered insolvent when its asset value falls below the cumulative value of debt payments due.

Black and Scholes (1973) state that the equity in a risky firm is equivalent to a call option on the net asset value of the firm. The net asset value is calculated as the market value of the firm's assets minus the claims on the assets which include traditional financial claims such as debt and other claims including erosion of asset values which may

result upon default. This model allows derivation, calculated from the distribution asset values of the default probability as the probability that asset values will be lower than the value of the claims on the asset.

One of the application of the option pricing model is the expected default frequency model (EDF) developed by KMV Corporation, known as CreditMonitor™. This program calculates the EDF during the forthcoming year to the next coming five years. Default is defined as the non-payment of any scheduled payment, interest or principal. The key feature is to incorporate prices of firms' debt and equity into consideration in addition to the traditional financial statement information.

The implementation requires calculation of asset values, asset value volatility, and claims on asset values. Using the option-pricing model, the first two variables can be estimated from the equity value and equity volatility.³ To simplify the model, the last variable, claims on asset values are represented by a single liability due at a single date.⁴ These three variables allow the default risk of the firm to be calculated through an EDF for each borrowing firm. Default occurs in some future period when the value of a firm's assets falls below its outstanding short-term debt obligations.⁵

³ This is due to the two theoretical relationships. First, the value of equity can be viewed as a call option on the value of a firm's assets. Second, the link between the observable volatility of a firm's equity value and its unobservable asset value volatility.

⁴ In practice, this is usually proxied by short-term debt outstanding. If it is assumed that all the debt is linked through cross-default provisions in the underlying documentation, then this simplification has more merit.

⁵ Based on the U.S. data, KMV found that the default point, the asset value at which the firm will default, generally lies somewhere between total liabilities and current or short-term liabilities. The relevant net worth of the firm is therefore the market value of the firm's assets minus the firm's default point.

Asset value, business risk, and leverage can be combined into a single ensure of default risk which compares the market net worth to the size 0 to 1 standard deviation move in the asset value. The firm will default when its market net worth reaches zero. The default probability is then determined by relating the likelihood of default to various levels of distance to default from data on historical default and bankruptcy frequencies. The default point is defined as the asset value at which the firm will default, generally lies somewhere between total liabilities and current liabilities. The distance to default incorporates three credit issues; the value of the firm's assets, its business risks, and leverage, and also incorporates the effects of industry, geography and firm size. Then, the default probability can be computed directly from the distance to default if the probability distribution of the assets is known, or, equivalently, if the default rate of a given level of distance to default is known.

The KMV model has several advantages. First, this model incorporates equity prices, which are forward looking while financial statements are inherently reflection of what happened in the past. Prices are usually formed by investors as they anticipate the future prospects of the firms, therefore, adding prices to find the default probability provides more predictive power. Second, market prices can be economically refreshed more often, whereas model based on accounting data have an irreducible quarterly lag. Further, it has the ability to estimate expected as well as unexpected default losses within a probability framework at specified confidence levels. Finally, its EDFs are ranged from 0.02% (2 basis points) to 20% and are reported with basis point precision, making for 1,999 different possible ratings which are much more than other rating agencies.

On the other hand, one limitation of the model is the requirement that the equity must be publicly traded. Another issue is whether the volatility of a firm's stock price can be used as an accurate proxy to derive the expected or implied variability in asset values.

2.3.2 Capital market based model

The most important innovations in this area are mortality rate model of Altman (1989) and aging approach of Asquith, Mullins, and Wolff (1989). These models seek to derive actuarial-type probabilities of default from historical data on bond defaults by credit grade and years to maturity. Traditional studies of high yield bond defaults have not properly considered the aging of the bonds. Altman (1989) measures the default rate by dividing the amount of defaults in a given year by the par value of all outstanding issues. This definition of default rate ignores the important effect of bond age on default risk. If bond default rates are not stationary through time but rise with bond age, and if there is a rapid growth in new issue volume year to year, default rates are severely biased downward by this measure. An alternative way to measure default risk is to consider defaults over time within a cohort of bonds issued at the same time.

In his most recent paper on high yield debt, Altman employs an aging concept, cumulative bond mortality, which utilizes cohort issue years. Cumulative bond mortality measures default rates on bonds that have been outstanding for equal periods of time and adjusts the size of the denominator for calls, maturities, previous defaults, and sinking funds. This technique avoids the aging bias of earlier studies.

There are two types of default risk in this model; cumulative versus marginal. The cumulative risk of default measures the total default probability of counterparty over the term of the obligation, while marginal risk of default measures the change in default probability of counterparty over a sequence of time periods. The cumulative default probabilities increase with a decline in ratings levels, but that marginal default risks decrease in the lower rating categories.

The traditional approach to bond valuation has been to link the required credit spread of an issue to its ratings supplied through Moody's or Standard & Poor's analysis. All of the rating agencies have adopted and modified the mortality approach. Such models can be extended to an analysis of the default mortality of loans, but have been hindered by the lack of a loan default database of sufficient size. For a firm or entity is not rated it is still possible to utilize rating agency default models and statistics. The bank can do what so called a homemade rating.

Rating agency default models can be used to identify the risk of default for counterparty with a known current rating. These models incorporate macro-economic cycles specific default risk as a function of two primary factors; recent rating and time to maturity of the obligation. However, since these models are based on historical default incident for a particular area or country, therefore, the application to other countries is questionable and need to be carefully investigated. Another shortcoming of these models is that these models required huge database in order to determine the default mortality rates, therefore, a shared database among financial institutions is needed.

2.3.3 Models based on the neural network system

Neural network models of credit risk discover potentially hidden correlation among the predictive variables, which are then entered as additional explanatory variables in the non-linear bankruptcy prediction function. The appropriate version of neural network being used is single-layer feed forward neural network system due to its less complexity comparing to other version of the neural network. The model can be used to find the correlation and relationship among variables for a credit rating replication because of its non-recurrent feature.

Two key elements in a neural network methodology are processing elements and interconnections. Neural networks consist of a potentially large number of elementary processing units. Every unit is interconnected with other units and each is able to perform relatively simple calculations. The network's processing result derives from their collective behavior rather than from the specific behavior of a single unit. The links are not rigid but can be modified through learning processes generated by the network's interaction with the outside world or with a set of symbolic signals.

The network is given a set of inputs generating a response that is compared with the response required. The weightings are not changed if the response obtained corresponds with the response required. If the difference exceeds a certain tolerance level, revisions are introduced into the weightings and learning start again, then a new case is input. The analysis of all the cases supplied constitutes the maximum extension learning cycle. Once the holdout set accuracy has been exceeded, the learning ends and the weightings are locked. The network has achieved a stable equilibrium configuration that represents its capacity to solve a

problem. The linear discriminant analysis discussed earlier can be considered as a subset of this approach. It is equivalent to a network made up of a single neuron that receives signals from the set of indicators and generates an output with a linear transfer function without transformation.

There are many advantages from the neural network approach. Neural networks are able to approximate the numeric values of the scores generated by the discriminant functions even with a different set of business indicators from the set used by the discriminant functions. Further, they have shown the accuracy, power, and flexibility. Coats and Fant (1993) use a limit number of financial ratios to duplicate the going-concern determination by accounting auditors. They utilize the cascade-correlation neural network approach to duplicate the auditor-expert conclusion of 94 manufacturing and non-manufacturing failed firms and conclude that the neural network clearly dominates the linear discriminant analysis. However, Altman, Marco, and Varetto (1994) comment that using auditing disclaimer report instead of the actual bankrupt firms to classify firms might be inappropriate. Khanthavit (1998) uses the neural network technique in predicting the bond rating of Thailand. He employs the same data set as in Vititayanon, Asawintarangoon, and Klinmali (1996). The results reveal that the single-layer feedforward neural network system can predict the credit rating more accurate than the logit model.

Although a widely application of neural network system, however, the major weak point of the neural network is its complexities. The extensive processing time for completing the neural networks training phase, the need to carry out a large number of tests to identify the neural network structure, as well as the trap of overfitting can considerably limit

the use of neural networks. Further, it requires homogeneity of data set to reduce noise, which sometimes it is difficult to find such a circumstance. Altman, Marco, and Varetto (1994) compare and contrast the two methods; neural networks and discriminant analysis, and conclude that the neural networks are not a clearly dominant mathematical technique compared to traditional statistical techniques, such as discriminant analysis. Consequently, the two competing systems are recommended to be used collectively.

2.4. The fourth wave: credit concentration risk

Concentration risk refers to additional portfolio risk resulting from increased exposure to one obligor or groups of correlated obligors (i.e., by industry, by location). Credit risk must be managed at both the individual and the portfolio levels. While there are already numerous methods and tools for evaluating individual, direct credit transactions, comparable innovations for managing portfolio credit risk are only just becoming available.

Banks and financial institutions have increasingly recognized the need to measure credit concentration risk in addition to the credit risk on individual loans. The early approaches to concentration risk analysis were based on three areas. First, the subjective analysis requires expert in the bank to use their feeling as to a maximum percent of loans to allocate to an economic sector or geographic location. Second, there is a limit exposure in an area to a certain percent of capital. Third, the migration analysis, measuring the transition probabilities of relatively homogenous loans, in a given pool, moving from current to any number of possible default states, which play a critical role in the recent CreditMetrics® ap-

proach. Recently, more potential for applying modern portfolio theory to loans and other fixed income instruments has been recognized.

3. The Evolution of Portfolio Concept for Loan Market

The development of portfolio concept for loan market starts from the seminal work of Chambers and Charnes (1961) which explain a simple balance sheet management problem. The bank seeks to maximize profits and has a choice between various classes of earning assets. Fried (1970) develops a model for bank portfolio selection that determines the mix of portfolio assets that would maximize expected bank profits subject to a number of legal liquidity constraints. Brodt (1978) provides a linear programming model based on Markowitz portfolio theory to solve the balance sheet management problem for banks. The risk measure adopted incorporates both the probabilities of deviations around the expected profits as well as the deviations themselves.

In Francis and Archer (1979) model, a bank's balance sheet is broken down into generic groupings of assets and liabilities, and the rates of return for classes of assets and liabilities are expressed relative to capital. The simultaneous treatment of assets, liabilities, and the imposed constraints provides a comprehensive framework within which portfolio optimization can occur. Although it is consistent with Markowitz's theories, the model suffers from many limitations. First, the assumption of liquidity of balance sheet assets and liabilities is unrealistic. Second, the abstraction of grouping significant proportions of assets, particularly loans into homogeneous securities is a significant oversimplification. In addition, an accurate estimation single-periods rate of return on illiquid assets is difficult.

Departure from earlier work based on balance sheet or portfolio of bond, the application of Markowitz portfolio concept has been extended to bank loan portfolios. However, there are some empirical difficulties. First, the information on loan return is not observable in the market except for some companies that have debt instruments traded on secondary markets. Second, the loan portfolio is much less liquid than equity portfolios then it is difficult to model correlations. Third, risk in a bank's loan portfolio is dissimilar to risk in an equity portfolio. Banks always view risk as the likelihood that an entity will not continue to service its debt obligations and repay that maturity, rather than the variability of expected returns. Therefore, there are many financial institutions incorporated with some consulting firms to develop a more reliable method in assessing the bank loan portfolios such as JP Morgan, KMV Corporation, and Loan Pricing Corporation.

3.1 CreditMetrics® approach

CreditMetrics® is a tool for assessing portfolio risk due to changes in debt value caused by changes in obligor credit quality developed by JP Morgan in 1997. CreditMetrics® estimates portfolio risk due to credit events. In other words, it measures the uncertainty in the forward value of the portfolio at the risk horizon caused by the possibility of obligor credit quality changes. It includes the changes in value, which is caused not only by possible default events of, but also by upgrades and downgrades in credit quality. Importantly, the program assesses risk within the full context of a portfolio basis, rather than on a stand-alone basis by addressing the correlation of credit quality moves across obligors. This allows a direct calculation of the diversification benefits or potential over-concentrations across the portfolio since it incorporates the set of

linked credit-related and other associated revenues in order to assess total return across an entire portfolio.

The measurement of credit risk is a three-step procedure in view of CreditMetrics® that results in an estimate of portfolio Value-at-Risk (VaR). The exposure profile of each asset, the volatility of portfolio value arising from changes in each asset's credit quality, and the determination of correlations between various credit exposures in a portfolio are combined to yield an overall estimate of risk.

Like the VaR models that have been developed and which are now widely used in the measurement of traded market risk, the approach which has been described above, in essence, generates a VaR estimate of credit risk. As in the case of market risk, statistics can be estimated to summarize the riskiness of the portfolios. It is possible to describe portfolio credit exposure in terms of confidence levels, just as it is for traded market portfolios.

3.2 Altman's Z"-score approach

In the traditional portfolio theory of Markowitz (1959), the effective diversification is achieved through the maximization of returns for given levels of risk or the minimization of risk for given levels of return. The required data for the optimization are historical returns and correlations of returns between individual stocks. In dealing with the fixed income portfolio analysis, Platt and Platt (1991) did some preliminary work for high yield junk bond portfolios by introducing a linear programming algorithm which maximized yield-to-maturity subject to a constraint as to the level of default risk and the degree of diversification.⁶

⁶ However, Altman and Saunders (1998) commented that the corporate bond managers have not utilized this concept and continue to invest based on traditional industry, size, and credit rating criteria.

Gollinger and Morgan (1993) develop their model for balancing the risk and return for a loan portfolio. The equivalents of individual stocks in their model are industries, where risk is defined as the volatility of industry credit quality as measured by the simple average ZETA score of the companies. Returns are calculated using publicly available loan pricing matrix data produced by the Loan Pricing Corporation. In determining rates of return, both industry credit qualities, as measured by ZETA credit scores, bond prices, and industry specific factors are taken into consideration. Estimations of covariance for industries are based on industry ZETA scores. Given these calculated returns, variances and covariance, determination of the bank's loan portfolio efficient frontier is reduced to a constrained optimization problem. However, this model ignores the aging of loans in the portfolios.

In the classic mean-variance of return framework, there is the problem with the distribution of possible returns when applying to the long-term fixed income portfolio strategies. While fixed income investor can lose all of the investment in the event of default, the positive returns are limited. On the other hand, if the measurement period of returns is relatively short and the likely variance of returns is small and normal, then it is more likely that this model will be valid. Therefore, Altman (1998) works on the Markowitz model based on short period of loan return and the unexpected loss of loans. The measurement of expected portfolio return can be calculated as yield-to-maturity minus expected losses from default of the issuer. The yield-to-maturity is a promised fixed return over time and expected losses are obtained from the analysis of credit rating. However, since most loans do not have a risk rating attached by the rating agencies, the loan portfolio analyst must utilize a proxy measure.

In determining the unexpected losses, the Z"-score model is proposed by Altman (1993). This model will assign a bond rating equivalent to each of the loans that could possibly enter the portfolio. The Z"-score approach is a four variable version of the Z-score model, consisting of working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, and book value of equity to total liabilities. It was designed to reduce distortions in credit scores for firms in different industries. The scores and rating equivalents will be used to estimate expected losses over time. The empirical results in Altman and Saunders (1998) confirm that the unexpected loss derived from the Z"-score model can be the alternative risk measure.

3.3 KMV's portfolio model

Kealhofer (1998) describes KMV portfolio model as the state of the art model being used by numerous banks around the world. This model aims at three objectives; to characterize the risk and return of a debt or loan portfolio, to determine what the optimal trading strategy should be for a defined set of trading or origination opportunities, and to optimize portfolios by shifting the view of the existing set of debt assets. Inputs to the model are the expected loss, unexpected loss and risk contribution for each asset, and each asset's expected return. The model calculates the portfolio's expected loss, unexpected loss, and loss distribution. Within the model, expected returns are measured as the expected percentage change in asset values while risk is measured as the standard deviation of returns. Expected loss is measured as the product of a loan product's default probability and its loss given default.

The unexpected loss on a loan is found by calculating the volatility in the value of the asset and transforming this into a rate of return.

Unexpected loss is a stand-alone measure of a loan's risk and reflects the expected average size of the deviation between actual and expected losses. In general, this difference is small but positive; however, every so often it is large and negative. Unexpected loss is thus the basic measure of loan risk. Whereas unexpected loss is an invariant measure of risk, the risk contribution is portfolio specific, i.e. it depends on the portfolio mix. Risk contribution measures the risk of a loan within a given portfolio. As a result of diversification, the risk of a portfolio is usually much less than the total of the stand-alone risks. In aggregate, a portfolio's unexpected loss is the sum of each loan's risk contribution. Risk contribution is related to the concept of beta, β , defined within the Capital Asset Pricing Model (CAPM). A loan portfolio's beta is:

$$\beta_{ip} = \frac{RC_i}{UL_p} \quad (3)$$

Where RC_i is the risk contribution made by asset i and UL_p is the portfolio's unexpected loss. Expected spread measures the component of loan's return which compensates for the risk of default. Expected spreads are calculated as the contractual return of the loan less the expected loss on the loan, less compensation for the time value of money, using the risk-free rate, such as LIBOR or the 90-day bank bill rate (Kealhofer et al., 1998). Optimization in the KMV model generates a series of optimal portfolios for each target level of portfolio risk. In aggregate, these optimal portfolios define the efficient frontier, and the highest level of expected spread for each level of portfolio risk. The model performs two types of optimization, global and trades. The former is the more familiar form of optimization and adjusts holdings of loans in the current portfolio to achieve a particular risk or return objective. Trades optimization, in contrast, assumes assets can be bought and sold, and origination

opportunities exist. By taking advantage of these, optimal balance sheet adjustments can be defined. The trade optimization feature provides guidance specific transactions assuming price information is available. Output from the model provides useful additional information such as the maximum Sharpe portfolio, minimum risk portfolio, as well as where the bank's actual portfolio is relative to the efficient frontier.

The move to a portfolio approach for measuring credit risk has a number of potential advantages. It can allow the quantification of concentration costs both from a total portfolio perspective and a marginal or individual transaction perspective. It creates a framework to evaluate all concentrations by firm, industry, sector, country or product. It allows users to evaluate trading and pricing decisions based on a transaction's contribution to portfolio credit risk. It provides a basis for risk based limit setting, capturing the effects of concentration and diversification, in place of traditional intuitively based limits which tend to be formed on obsolete stand-alone exposure to each obligor.

Significantly, models of this type allow financial institutions to evaluate their risk-taking capability more effectively, leading to more precise measures of capital requirements. The increased focus on both the measurement and management of credit risk may also prove to have implications for the longer run liquidity in credit markets, the emergence of a mark-to-market approach to credit positions and the more rational pricing of credit risk. Finally, methodological developments of this type may encourage supervisors to develop a regulatory framework which more closely reflects the true economic risks faced by banks and other financial institutions as a result of their credit exposures.

The key limitations in modeling credit risk are, firstly, the lack of comprehensive default data. Where a firm has its own information that is judged to be relevant to its portfolio, this can be used as the input into the model. Secondly, the model also ignores downgrade or migration risk, for instance, the fall in the prices of the security resulting from declines in credit quality are ignored. Also, causes of default derived from capital structure of individual firms in the portfolio are ignored.

4. Conclusion

This paper critically reviews the evolutions of credit risk measurement literatures on the individual loan and loan portfolios of banks and financial institutions. The evolution of the credit risk measurement can be grouped into four generations. The first measurement approach is based on a stand-alone unit of expert system. Stand-alone credit risk measurement involves a growing array of analytic techniques from univariate, qualitatively weighted quantitative systems, and qualitative variable credit scoring systems to an increase in number of more sophisticated procedures. This approach is primarily ease of use; however, it tends to be bias and pessimistic about the credit risk of the borrowers.

The second development is accounting based credit-scoring system, which relies on key accounting ratios derived from financial statement of the potential borrowers. These measurement systems have included multivariate regression, discriminant and logit statistical models. All these techniques involve credit-scoring procedures, assessments of negative event probabilities. These models have performed quite well in many cases, but they may fail to pick up those data that would be reflected in market values. An alternative model uses theory such as option-pricing

theory to relate movements in the price of a borrowing firm's equity to an estimate of the distribution of the market value of the firm's assets. This asset value distribution, in turn, is used to estimate the probability of the firm becoming insolvent. However, it has a limited scope on individual loans.

The more recent development is to measure credit concentration risk at portfolio level, which allows financial institutions to assess their risk-taking capacity more effectively. Credit risk can be managed at the portfolio level. The maximization of returns for given levels of risk or the minimization of risk for given levels of return in the traditional portfolio theory of Markowitz (1959) is inappropriate in working with loan portfolio level due to the non-normal property of the return distribution of loan. The proxy for risk is no more the variance of the return, but rather the unexpected loss on individual loans or portfolios of loans. In all portfolio models, however, the illusive ingredient is to properly estimate risky event correlations between loans, which are difficult to identify.

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