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Recent Development in Credit Risk Measurement and Credit Risk Modelling with Respect to Different Types of Borrowers

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Abstract: This paper delves into the intricacies of credit risk measurement and modeling, particularly focusing on the challenges faced in assessing credit risk for small and medium-sized enterprises (SMEs) and retail borrowers. It begins by outlining traditional models of credit risk measurement and proceeds to a critical analysis of their application in the context of SMEs and retail borrowers. The paper highlights the limitations of most models in accurately assessing credit risk for these segments and explores the reasons for their inapplicability. It further examines the motivations of banks to develop their own credit models and offers insights into how this can be achieved effectively. The paper concludes with a summary of the key findings and implications for future research and practice in credit risk management.

1. Introduction

Credit risk refers to the possibility that a borrower failing to perform the contract for some reasons, resulting in the breach of contract[1]. Borrowers expect to pay current debts by using future cash flow and it may not guarantee borrowers have enough money to repay debts. It may cause banks and investors suffer losses[2]. Credit risk assessment method has existed for nearly 50 years[3]. In general, since financial innovation and derivatives grow rapidly, credit risk measurement are essentially important to organizations (such as banks) and special groups in business area (such as issuers and investors)[5]. Traditional models does not accord with the modern credit rating measurement. Thus, it developed into four major methods, which are KMV model, CreditMetrics, Credit portfolio View and CreditiRisk+. However, most models are suitable for measuring the credit risk of large companies. Therefore, developing an appropriate measurement and modelling has become a thorny but critical issue. Hence, the analysis about the development of credit risk measurements and modelling in this paper have a profound significance.

In this paper, firstly, we begin with introducing some traditional models of credit risk measurement. Secondly, we review and in depth analysed credit risk measurement and credit risk modelling in small and medium sized enterprises (SMEs) and retail borrowers. Then, we elaborate on the suitability of various models for SMEs or retailers and give some suggestions. Moreover, we also explain that why most of models are not applicable to SMEs and retails. Thirdly, we discuss motives of banks to develop their own credit model from three different aspects and give some suggestions. Finally, the paper concludes in the last section.

2. Credit Risk Measurement

2.1. Expert system and multivariate methods

Credit risk measurement has significantly changed over the last 30 years. Traditionally, most financial institutions totally count on subjective or expert systems to assess the credit risk. To be more specific, bankers used several characteristics of borrowers, such as Character, conditions, capital, capacity and collateral (5Cs)[6]. However, traditional expert systems do not point out which factor is the determinant in forecasting PD (Performance data)[7]. Thus, since the 1970s, the western countries established various models on credit risk measurement and management. In order to achieve the analysis of credit risk measurement in qualitative and quantitative level, there are different models can be used for credit risk measurement and credit rating. The first pioneers are Beaver (1967) and Altman (1968) in this field. They used a series of financial ratios to developed univariate models. Although the univariate predictive model is relatively simple, the financial status of a company is reflected on various financial indicators. No single ratio can summarize the status of the company. Therefore, this method often leads to the use of different predictors for the same company to draw different conclusions. Subsequently, univariate methods replaced by multivariate methods to predict credit risk. In the initial study of multivariate analysis, Altman (1968) selected five variables in 22 potentially useful financial ratios by using a multiple discriminant analysis technique (MDA), then the best prediction of company's bankruptcy can be provided by these variables[8]. The five variables were classified into five standard ratios categories, including liquidity, profitability, leverage, solvency and activity ratios[8]. Altman developed Z-Score models by those five variables in 1993 and this method becomes a popular statistical technique.

2.2. Credit risk measurement for SMEs

In 2007, Altman used MDA model and logistic analysis to analyse small and medium sized enterprises (SMEs) in the U.S. In this research, it seems that when using the same predictors, the logistic models have higher ability to distinguish default and non-default SMEs compared with MDA models[19]. The study shows that the overall accuracy level (AR) of unlogged variables are lower than logged variables and the proportion of defaulted corporations sort as non-defaulted reduced. Ohlson (1980) pointed out that the logistic model may be more suitable for default prediction because it can get a score between zero and one, so it makes the prediction of customer defaults very simple[13]. There are two problems in MDA models, firstly, it violates two basic assumptions of MDA. Secondly, the standardized coefficients cannot be explained like the slopes of a regression equation. It may show that MDA is not applicable to the analysis of default in SMEs. Then, Altman used well-known statistical techniques to select U.S. SMEs and use logistic deal with five financial ratios[20]. They use five financial ratios to create a credit risk model for SMEs. It demonstrated that this new model is nearly 30% higher than the general model in forecasting default and non-default SMEs. It seems that it is necessary to separate the modelling of SMEs credit risk from large enterprises.

In recent years, credit risk measurement model can be divided into four major methods: KMV model, CreditMetrics, Credit portfolio View and CreditiRisk+[9]. The KMV model and CreditMetrics model are the two most popular credit risk measurement model in the international financial community. Compared with CreditMetrics model, the advantage of KMV model is that it relies on modern options theory, utilising full capital market information to forecast default. Wang (2002) indicated that KMV model was better than other models for analysis of default in listed companies. It could reflect the current credit status of listed companies in a more effective way. In addition, Ma (2006) found that KMV model is more applicable to the default warning of Chinese listed companies than the Logistic and Fisher model[16]. Because logistic model exists some drawbacks, it may cause prediction errors, such as a large number of samples and Multi-collinearity problem[10]. However, although it can quantify and analyse the credit risk of the company, this model is particularly suitable for the credit risk rating of listed companies. When applying to non-listed companies, it is necessary to adopt some accounting information or other indicators to replace some important variables in the model. In addition, it assumes that the company's asset value obeys a normal distribution, but actually, the asset value of a company will generally show non-normal statistical characteristics. Even if there are some shortcomings, KMV still becomes a model that is more suitable for predicting SMEs' breach of contract in many models. Because in KMV model, although financial data and credit information are inadequate in most SMEs, credibility, macroeconomic conditions and stock prices can still be used to measure credit risk[5]. In general, traditional KMV model only simply relied on stock price fluctuations to determine equity value volatility (σ_E). However, it ignores the changes in net assets per share and effects changes in equity. It seems that some errors will appear. Chen (2010) developed a new approach to change the parameter, which proved that the KMV model could be more suitable model, which accurately forecasts credit risk in the listing of SMEs, especially in the China market. In his research, the price of tradable shares (such as equity donation, distribution and orientation repurchase in the split share structure reform) and equity changes are considered, which effectively increased the accuracy of σ_E calculations. Then, the distance to default could be calculated more precisely. Through using the new KMV model, default distance is closer to the true value, which means it would accurately determine whether to default. It also finds that asset size positively correlated with credit risk, so it is possible that KMV model will effectively discriminate the credit risk of listed SMEs in China market [4].

According to above two new models, both two new models are analyse and test credit risk in specific markets. For example, Altman's SMEs model examine American SMEs. It only demonstrates that the new model is suitable for American SMEs. Due to different market leads to different data in SMEs market, it is difficult to establish a general model to analyse the credit risk of SMEs. Therefore, it requires a large number practice and theory to improve the credit risk measurement.

2.3. Credit risk measurement for Retail Borrower

Retail credit market is a special market that experts cannot analyse retail by using simplified analysing large companies' models[11]. Retail borrowers generally borrow less money, it will lead to a minimal credit risk on any individual loan. Besides, any loss of retail loan may not result in bankruptcy of bank. Thus, because banks may determine that the cost of credit risk of each retail borrowers could be greater than the loss of default, it may not be worth to determine the credit risk of individual retail loans. In addition, some variables, such as the probability of default (PD), the loss given default (LGD), and exposure at default (EAD), are different from that of companies, hence these variables cannot be applied to measure retail borrowers[12].

Before various modern models measure the credit risk of small businesses, a large number of banks will collect and analyse the balance sheet and income statement data or 5Cs method to judge the credit risk of the small company. However, in general, small businesses may miss some data, which makes it difficult for banks to judge credit risk precisely. Thus, artificial neural networks have been developed, it uses historical repayment information and historical default data to determine probability of default[11]. However, each time the credit risk of a new loan is assessed, its weight plan will be updated. It leads to higher evaluation costs. Another method is internal rating system, generally, banks have their own internal rating system to determine credit risk[14]. Although it may be more convenient to classify retailers for rating, the rating system is relatively crude and chaotic. Most loans are classified as pass / Performing and only a minority of loans rated as other assets especially mentioned, substandard, doubtful, and loss. On the one hand, retail borrower will have different credit risks in different banks. Especially in small banks, they tend to use their own rating system to determine retailers. Boot's (2000) study indicates that small banks can get the proprietary information about their clients to make a special contact with retail borrowers[18]. This relationship may affect credit risk rating, it could make retailers borrowing easier. On the other hand, after internal rating, the bank needs to determine interest rate of the loan. Due to the existence of the special relationship, the interest rate of banks may be reduced, leading to a decline profit in banks. Berlin and Mester (1998) suggested that this relationship may impair the profitability of lending institutions due to low interest rates, the relationship between the bank and borrowers may cause a loss if banks' profits[17]. It is obvious that this method is neither scientific nor feasible.

Although there are many models that can be used to measure risk, the study of retail credit risk measurement is not perfect. In recent researches, many experts and institutions use KMV model. Using Moody's RiskCalc and CreditRisk+ to analyse retail credit and then discuss the possibility of simplifying the model. In KMV model and CreditRisk+ model, asset values and asset volatility are important for these models to analyse credit risk. Due to retail borrower does not have equity prices, the asset values and asset volatility cannot be used to estimate[11]. Thus, it may not suitable for evaluating retail. However, in International Swaps and Derivatives Association (ISDA) and the Institute of International Finance (IIF) study, many banks used the KMV Portfolio Manager model and the internal model to analyse the small retail (up to $5,000) and large (up to $30,000) retail[21]. It shows that the KMV model predicted a slightly lower total loss for portfolio of large retail loans than bank internal models (2.3% versus 2.7%), while a slightly higher risk for portfolios of small retail loans (3.6% versus 3.2%). There are some not significant differences. Under certain conditions, it could be used to predict the credit risk in the retail markets. Furthermore, Moody's RiskCalc may apply to test the possibility of default. Moody's firm creates a large number of credit research databases (CRD), which means that the different companies will have separate models. Through analysing previous defaults, banks are able to select the financial ratios that are most important to determine the default of the borrowers. However, Moody's firm found that there are significantly difference between retail markets and other markets. One of a major reason is that retail borrowers do not have reliable financial statements, so it may result in erroneous assessments by applying existing models in retail market. Therefore, the existing credit risk measurement models does not in full compliance with risk characteristics and data requirements in retail credit measurements. These models often need to use the price of equities or other financial information. Therefore, banks should select the most suitable model through the characteristics of the different retail business.

3. The motive of bank for developing credit model

With the continuous development of the society, the credit system has been perfected. However, due to a large number of retail and individual loans, it is not possible to use the general credit model to measure the risk. Thus, in the new Basel Accord, it suggests banks build their own models by risk parameters such as the probability of default (PD), loss given default (LGD) and exposure at default (EAD)[15]. In addition, The Office of the Comptroller of the Currency (OCC) always require banks to use their own internal rating system to rank the credit risk. It helps to promote the modern risk management. Similarly, banks should also update the rating system in order to reduce risk and prevent losses. According to a survey of JPA Company, the majority of banks are losing money because of unsuccessful risk management, the main reason is the lack of basic data. The lack of data has made it difficult for banks to run credit ratings[11]. Therefore, banks should establish a unified database and management information system as soon as possible to prevent losses and reduce the risk of default. Moreover, establishing their own credit risk models can provide a fair and objective information for investors. Banks can assess companies according to their own models so that investors can learn about the real information of the company based on the bank's rating system. To some extent, it can reduce financial risk. The information that database provided also helps the financial supervision departments such as the central bank to supervise, which is beneficial to the stability of the financial market.

The purpose of banks developing their own model is to quantify the customer's credit risk. General models are unrepresentativeness and may cause errors when analyzing different clients. Hence, it is difficult to quantify risk accurately. It could also lead to a slow process and time wasting. For example, if someone wants to apply for a credit card, the bank need to consult a credit agency to analyse this client's income and cash flow history. Then compare these data to assess credit risk. It will waste amount of time and money and affect the efficiency of applicant's credit card. Banks should develop their own credit risk models to increase work efficiency. If the credit rating is accurate, it will improve bank operating efficiency and increase profits. Besides, it can maintain a high financial flexibility even if the bank are suffering a loss. Therefore, banks should give priority to develop their own rating system[1].

4. Conclusion

The trend of SMEs and retails choosing loans are significantly increased. Most credits need to be evaluated, but traditional model is not suitable for measuring credit risk in SMEs and retails. In recent studies about SMEs' credit risk model, due to some missing financial data, the new model measures the credit risk of SMEs by replacing financial variables. It provides a new method to analyse SMEs, but this new model is only used for analysing in specific markets For example, the new KMV model only analyses the applicability in Chinese market. Thus, banks should consider the recent research results about SMEs and combine the different methods, such as rating systems and scoring. It will lead to a better management in credit risk. For retails, in ISDA and IIF study, differences between the KMV model and the bank internal model are not significant, KMV model could be a good method for analysing retails. Besides, Moody's RiskCalc and Credit Risk+ need a database to analyse the retail more effectively. Thus, lacking of databases is the main problem in existing models when we analyse the retails. Furthermore, it illustrated that the credit risk of SMEs and retails are different from large companies. In addition, it confirmed the measurements of credit risks of SMEs, and retails need special models. In the last part, we also discussed the motive of bank for developing credit model from two different perspectives. First aspect is reduction of risks and losses. Through bank's own credit models, they are able to reduce default risk because more information and more data about clients are provided. Another aspect is improvement of efficiency and the decline of costs. Establishing bank's own credit models replace the process of consulting external agencies. Banks may prefer to believe in their own models, because they can directly analyse the credit risk based on practical situation. Besides, the cost of credit models' establishing process are one-off, while the profit it brings is sustaining.

References

[1] Bluhm, C., Overbeck, L., Wagner C., (2002) An introduction to credit risk modeling. Chapman and Hall/CRC.
[2] Will, G.A., Ilya A., Strebulaev B.C., (2018) Financing as a supply chain: The capital structure of banks and borrowers

[J]. Journal of Financial Economics, 129(3):510-530.
[3] Fatemi, A., Fooladi, I., (2006) Credit risk management: a survey of practices. Managerial Finance, 32(3), pp.227-233.
[4] Wang, Q., Chen, J., (2002) The study of credit risk model and pricing method, ModernFinance and Economics: Journal of Tianjin University of Finance and Economics 22 (4) 14–16
[5] Chen, X., Wang, X., Wu, D.D., (2010) Credit risk measurement and early warning of SMEs: An empirical study of listed SMEs in China[J]. Decision Support Systems, 49(3): 301-310.
[6] Afrane, S.K., Owusu-Manu, D., Donkor-Hyiaman, K. A. and Bondinuba, F. K., (2014) Towards Innovative housing financing in Ghana: an evidence-based from South Africa's pension housing financing system. Public Policy and Administration Research. 4(4), 97-110
[7] Arndt, Jamie, Sheldon Solomon, Tim Kasser, and Kennon M. Sheldon (2004), "The Urge to Splurge: A Terror Management Account of Materialism and Consumer Behavior," Journal of Consumer Psychology, 14 (3), 198–212
[8] Altman, E.I. (1968) Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The journal of finance, 23(4), 589-609.
[9] Markus, K. and Bernd, R., (2001) Comparative Analysis of Alternative Credit Risk Models – an Application on German Middle Market Loan Portfolios, Journal of Banking & Finance, 24(2), 59-117
[10] Guajardo, M. and Rönnqvist, M., (2015) Operations research models for coalition structure in collaborative logistics. European Journal of Operational Research, 240(1), pp. 147-159.
[11] Allen, L., Gayle, D., and Anthony, S., (2004) "Issues in the credit risk modeling of retail markets." Journal of Banking & Finance 28(4): 727-752.
[12] Ohlson, J. (1980) Financial Ratios and the Probabilistic Prediction of Bankruptcy, Journal of Accounting Research, 18(1); 109-131
[13] Van Gestel, T., Baesens, B., Van Dijcke, P., Garcia, J., Suykens, J.A. and Vanthienen, J., (2006) A process model to develop an internal rating system: Sovereign credit ratings. Decision Support Systems, 42(2), pp. 1131-1151.
[14] Li K., Zhou F.Y., Li Z.Y., Yao X., Zhang Y.S., (2021) Predicting loss given default using post-default information, Knowledge-Based Systems 224.
[15] Ruowei, M., (2006) Testing KMV on the financial distress of listed companies in China, Application of Statistics and Management 25 (5) 593–601.
[16] Berlin, M., Mester, L. J., (1998) On the profitability and cost of relationship lending. Journal of Banking and Finance 22, 873–897.
[17] Boot, A. W. A., (2000) Relationship banking: What do we know? Journal of Financial Intermediation 9, 7–25.
[18] Altman, E. I. and Gabriele Sabato (2013). Managing and Measuring Risk: Emerging Global Standards and Regulations after the Financial Crisis. Managing and Measuring Risk.
[19] Altman, E. I. (2006) "Default recovery rates and LGD in credit risk modeling and practice: an updated review of the literature and empirical evidence." New York University, Stern School of Business.
[20] IIF/ISDA, (2000) Modeling credit risk: Joint IIF/ISDA testing program, Institute of International Finance and International Swaps and Derivatives Association, February.