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A Warning Model of Centralized Credit Default in Commercial Banks

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Abstract

The development and operation of commercial Banks have a great relationship with risks, which can not only bring profits to Banks, but also bring about crisis. Among them, credit risk is the most important risk. The traditional evaluation model is aimed at individual default risk, however, due to the changes of macroeconomic and between individuals infectious, centralized credit default has also become a topic worthy of thinking deeply. One of the most important factors leading to the concentration of credit default is the infectivity of individuals. In this paper, the author mainly discusses the effect of the infection of individuals on the centralized credit default, and constructs a new warning model with the impact model and establishes a reasonable warning field. When the time interval of two consecutive defaults is less than that of the warning region, the bank should take preventive measures immediately.

Keywords:
Centralized credit default
Infection model
Early warning model.

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1. Introduction

Credit risk is the main risk of banks, and there have been bank crisis caused by credit risk. The study found that crises tend to occur because banks do not pay too much attention to borrowers' default, and when the loan default rate rises significantly, the amount of loans is not decreasing. In fact, when faced with this situation, the bank should no longer be of concern is how to reduce the loss of individual defaults, but should focus on a certain moment in the default event to protect against it. Therefore, this paper mainly discusses the centralized credit default caused by the infection among individuals, and the early warning model for prevention.

2. Literature Review

A default by an individual may lead to a default by the individual involved, thereby triggering a central default. It can be shown that if company a defaults or goes bankrupt, it will have a negative impact on the company of a in the same industry to a certain extent, which will lead to the occurrence of other company defaults in the industry of a. The risk of default can be spread across industries, as well as between industries. When industry companies often occur in A company and the industry of B dealings, the company A default at the same time, to some extent reflects the industry negative situation of B, B will affect the industry management, this is the general transmission (Peiling, 2016). And trading for infectious risk, can be called the risk of default contagion, is refers to the company$a$, b. Creditor-debtor relationship between or company b to company a secured party, when company a default occurs, will directly impact on the operation and development of company$b$, which can lead to company b default. At the same time, the company default of b industry will impact to conduct transactions with other companies, resulting in widespread defaults. It can be represented by Figure 1.

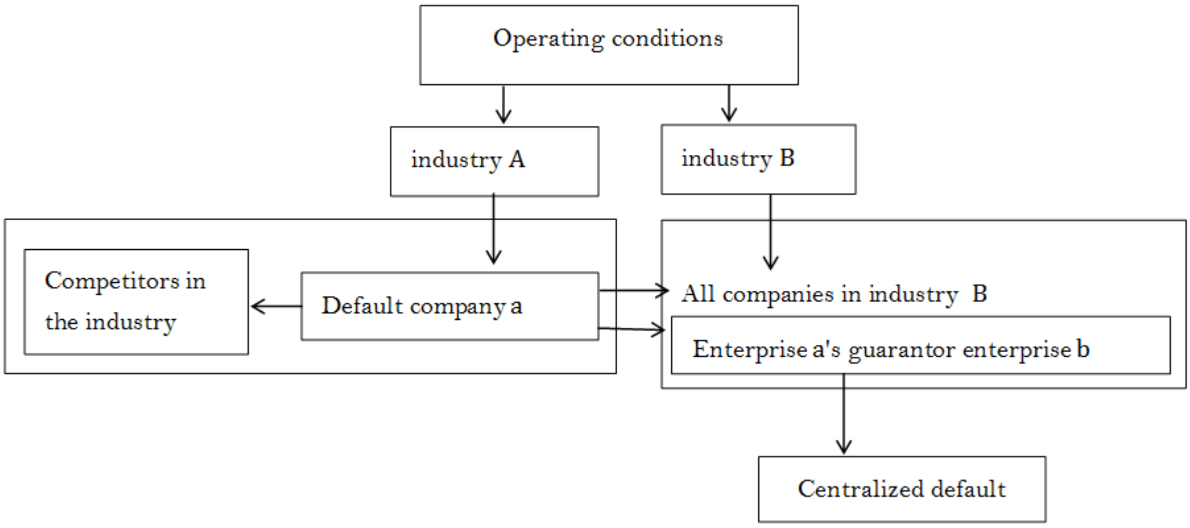

Figure-1. Risk contagion model.

Source: Peiling (2016).

On the basis of Figure 1, this article stipulates that when a company's return on assets and the standardized return rate is reduced to a certain level, the company will default on its debt.

Consider the return on assets, assuming that the return on assets of a given company follows a normal distribution$N(\mu, \ \sigma^2)$. The probability of default occurs:

$$p = P(R < K) = \phi(K) \qquad (1)$$

One of R is through standardized processing companies return on assets, K is able to yield under the minimum value, namely the default border (Jinbao, 2014).

In order to see the effect of individual infectivity on the probability of concentrated credit default, this paper considers a loan portfolio consisting of only two loans. First of all, the first case, the transmission hypothesis does not exist between the two companies, the company return on assets by the industry. A, B, company B by industry C, D, the influence of company a, B's return on assets can be represented with the following formula:

$$R_2 = \alpha_{2,3}R_{(3)} + \alpha_{2,4}R_{(4)} + \lambda_2\varepsilon_2 \qquad (2)$$

$$R_2 = \alpha_{2,3}R_{(3)} + \alpha_{2,4}R_{(4)} + \lambda_2\varepsilon_2 \qquad (3)$$

In formula(2),(3), R_i represents the standardized index return of the ith industry, and the correlation matrix of the index return of the industry is $\Sigma = (\rho_{i,\ j})$, $\rho_{i,\ j}$ is the ith, the correlation coefficient of the yield of the j industry index, $\alpha_{(i,\ j)}$ represents the index yield of the jth industry to the interpretation weight of the ith industry, ε_i denotes the specific part of the company's rate of return other than the industry, λ_i is ε_i interpretation weight. In the second case, based on the original industry influence, and considering the infectivity of the individual. it is assumed that the earnings change of company 1 will affect the earnings of company 2. In order to make the analysis easier, we can make the assumption that the income change of company 2 will not affect 1. Therefore, on the basis of the constant return rate of company 1, the company can be represented as the part of the company except the influence of the industry.

$$\varepsilon_2^* = \beta_1\varepsilon_1 + \sqrt{1-\beta_1^2}\,\varepsilon_2 \qquad (4)$$

β_1 represents the impact weight of company 1 on company 2, the greater the value of β_1, the stronger the contagion effect between companies. Considering the infectivity of individuals, we can get the following model:

$$R_1 = \alpha_{1,1}R_{(1)} + \alpha_{1,2}R_{(2)} + \lambda_1\varepsilon_1 \qquad (5)$$

$$R_2 = \alpha_{2,3}R_{(3)} + \alpha_{2,4}R_{(4)} + \lambda_2\beta_1\varepsilon_1 + \lambda_2\sqrt{1-\beta_1^2}\,\varepsilon_2 \qquad (6)$$

With two models for testing, can draw between individuals has greatly influence on credit default of infectious.

3. Research Method

As one of the main contents of the reliability theory, the impact model is used to depict the life characteristics of the system operating in a random environment and subjected to constant external shocks (Jianming & Hongmin, 2008). Banks concentrated defaults can run as in random environment and continue to receive the outside impact system, the central problem is system failure time, so in the case of early warning and centralized credit default, choose δ- impact model is set up is very reasonable.

About centralized credit default, this scenario is taken into account in the δ- impact model: the impact of the system encounters a series of random time, when the interval between two times fall into is associated with a given amount of a δ failure domain, the system failure. On the premise of the normal business operation of banks, this article assumes that began when timing system into the steady state. Namely, whether the first shock interval in the failure domain, it will not result in system failure. Based on the infectious situation of individuals, it is not difficult to know that two defaults are not independent. In order to make the model calculation more convenient, we can assume that two default events are independent and calculate the failure domain. Therefore, this article assumes that the default is a poisson process, namely the default to N parameters for λ homogeneous poisson process $N(\tau)$.

Set T for Banks to engage in a business of time, by using the properties of a poisson process, the bank's survival function can be obtained as follows, in the moment t, bank continues to carry out the probability of the business.

$$S(t) = P(T \geq t) = e^{-\lambda t}\sum_{k=0}^{[t/\delta]+1}\{\lambda[t-(k-1)\delta]\}^k / k! \qquad (7)$$
$$(\tau \geq 0)$$

From this equation, it can be seen that with the increase of t, the probability of banks carrying out business will decrease continuously, while $F(t) = 1 - S(t)$ is increasing. And as t go to infinity, the probability of $S(t)$ going to 0 is 1.But in fact, with the increasing of time, the banks will not end a project, so we can put the business time to time t_0 , the survival of the imaginary function as within the time $[0, \ t_0]$ with probability 1 in order to develop the business.

We should avoid two possible errors in the selection process about δ. The first is to oversize the value of the value, which will cause the bank to be unable to judge in time even if there is a concentrated default. A second possible error is δ will get too much, when there is no centralized default occurs, immediately stop the business, is not conducive to banks normally conduct business and make a profit, so choose the appropriate δ value is very important. At the same time, the selection of t_0 and δ has a certain value, if selected $t_0 \leq \delta$, so if there was a default within the t_0, then it will lead to two default time interval is less than δ, the system will failure, namely that will occur as long as the default system failure, this will make banks become too sensitive, to carry out a series of business. So we're going to have less than t_0.

In combination with the above conditions, we should make the following conversion of the following ideas before determining the final value of δ:

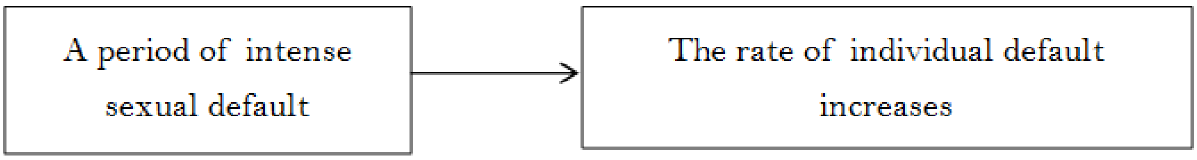

Figure-2. Ideogram.

Source: Guoxing, Peng, Yingluo, and Ju-e (2013).

If the default speed increase, at some point t_h will be from the original speed λ to λ' breach of contract. When λ' to a certain degree, the ratio of real survival function and hypothetical survival function can close to 0, allowing banks to large probability and terminate the business to continue. If λ is constant, the bank will continue to conduct business in this period of time, after this period of time, the bank will be back to the environment and risk assessment, make it the next time period to the probability of less than 1. If in this period of time, λ has changed, the bank want to t_0 or is found ahead of schedule, so I hope that when $t=t_0$, imaginary survival function and maximum ratio of survival survival function, can get early warning model for:

$$\text{Max}\Theta = S(t_0, \delta, \lambda) / S(t_0, \delta, \lambda') \qquad (8)$$
$$(0 \leq \delta \leq t_0)$$

According to that, $S(t_0, \delta, \lambda)$ and $S(t_0, \delta, \lambda')$ respectively with upper and lower bounds, shows that the equation has a solution (Guoxing et al., 2013). This model is based on individual independence, and when considering the infectivity of individuals, the time interval between the two defaults will become smaller, indicating that the model is reasonable for the existence of infection among individuals.

4. Results and Discussion

To test the accuracy of the model, based on historical data, this article assumes that a default event happens once a year, which is $\lambda = 1$ time/ year. Set default occur, the bank is willing to bear the beat of default rate of $\lambda' = 5$ times/year. According to the bank's focus on credit risk early warning model can be concluded that the δ^*= 0.084. When early warning domain the δ is smaller than the δ^*, with the increase of the δ, Θ also gradually increased. When the bank makes the δ increase, the imaginary survival function decreases less than the real survival function, so the ratio of the function becomes larger. When early warning domain the δ is greater than the δ^*, survival function decline at the same time, the hypothetical survival function also falling fast, cause no centralized credit default occurs, also issued a warning signal. These two scenarios verify that the model can issue a warning even after a centralized credit default occurs.

5. Conclusion

Centralized credit default can make banks in crisis, and lead to focus on the most important factor is the individual credit defaults between infectious, contagious between research. This paper expounds on the individual's influence on the concentration of credit risk of default, and established the corresponding early warning domain according to the model, when the interval between two successive events of default in early warning domain, then takes action. It is hoped that the credit risk aversion of commercial Banks has certain reference significance.

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