Bank efficiency evaluation and bankruptcy analysis model

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Abstract. Banks play an important role in the economic and social development of a country, and bank failures can have numerous adverse effects on businesses and individuals. However, the frequency of international bank failures is so high that the analysis and prediction of the causes of international bank failures has received a lot of attention from many managers and academic researchers. This article selects data on 64 indicators of existing or failed banks in Poland from 2017 to 2021, and proposes a bank efficiency evaluation and bankruptcy analysis model in order to analyze the efficiency of bank failures in the context of studying the inputs and outputs of each bank, after which the five most important causes of failure are selected, based on which a failure risk prediction model is developed, through which representative banks are selected and specifically applied to other banks. Based on the principal component analysis method previously done, fuzzy component analysis was introduced for specific evaluation, while for the data of these banks to be used for the prediction of the risk of other banks, a banking system was created in this paper and a risk contagion model was introduced. Finally, specific calculations were performed for the time series model, and cluster analysis was performed using its residuals as the discriminant criterion to determine whether they came from the same bank. The research in this paper is more accurate in predicting the possibility of bank failures, and the approach used in this paper is more risk-averse than current techniques, minimizing losses from bank failures and providing more effective protection for citizens' property.

Keywords: Efficiency Evaluation, Bankruptcy Analysis, Principal Component Analysis Method, Fuzzy Component Analysis.

1. Introduction

Commercial banks play an extremely important role in the economic growth and development of a country due to the provision of financial intermediate products and means of payment. Currently, the domestic banking industry is facing fierce competition from foreign banks and other overseas financial institutions face to face, and the issue of bank competitiveness has become the core issue related to the development of China's banking industry. With different sizes of domestic banks, different policy environments, different institutional arrangements, different sense of bank competition, etc., it is a major issue for bank supervisors to implement effective supervision on them. It is a macro environment necessary for the development of the banking industry for regulators to understand bank efficiency information and implement targeted regulatory measures and development policies. Correct evaluation of banks' operational efficiency is the basis for effective supervision. The banking system in China is a structure in which state-owned banks and emerging banks, domestic and foreign banks coexist and develop, and they all have a general division system, so the banking industry is highly competitive. The management of a bank wants to expand the market share of this bank and increase its revenue, it must improve the operational efficiency. How to evaluate bank efficiency and the efficiency of its branches is naturally before the bank managers. Finding scientific and reasonable methods and tools for bank efficiency assessment is always one of the tasks of managers. At the same time, banks are faced with the choice of their customers. Customers always choose banks that operate efficiently, because the credit base of such banks is more guaranteed. Therefore, rational customers always try to find out some valuable information about banks in their city, and efficiency is one of them. The results of bank efficiency evaluations are part of the public information.

In this paper, we conduct bank efficiency evaluation and bankruptcy cause analysis, first we compile data from 64 indicators of existing or failed banks in Poland from 2017 to 2021 that are suitable for input and output, and analyze each bank's failure efficiency to find the five most influential indicators. Then, we analyze the results of the comparison and build an accurate failure risk prediction model, and then select the 20 existing banks and 20 failed banks that are most representative of the bank data center in 2021 to predict the failure risk of other banks.

2. Model Design

2.1. Model assumptions

(1) Assuming no unforeseen large dollar amount policy changes are considered.

(2) 64 indicator data for existing or failed banks in Poland from 2017 to 2021 are assumed to be free of bad points, i. e. incorrect data.

(3) Data of each bank does not affect each other

2.2. Symbol Description

The symbols mentioned in this article are shown in Table 1 below.

Table 1. Description of symbols

Symbols	Specific meaning	Symbols	Specific meaning
X1	Interest income/earning assets	X8	Assets per capita
X2	Net interest income/earnings assets	X9	Allowance for loan losses/loans
X3	Profitability on Assets (ROA)	X10	Allowance for loan losses/non-performing loans
X4	ROE	X11	Non-performing loan ratio
X5	Retained earnings/equity	X12	Capital Adequacy Ratio
X6	Net write-offs/loans	X13	Core Capital Adequacy Ratio
X7	Income before taxes/net write-offs		

3. Modeling and solving

3.1. Selecting appropriate input-output data and evaluating bank efficiency

3.1.1. Model preparation

The dataset is about bankruptcy forecasting of Polish companies. The data used in this paper were collected from the Emerging Markets Information Service (EMIS, [Web Link]), a database containing information on emerging markets around the world. insolvent companies were analyzed for the period 2010-2020 and companies still operating were evaluated for the period 2017-2021. Based on the data collected, the classification was based on the forecast period.

3.1.2. Model building and solving

(1) Data envelope modeling

We obtain a model for the study of commercial bank failure efficiency using the following model transformations. [1] The specific model is as follows.

BCC model: A constraint is added to the CCR model to turn it into an efficiency evaluation model under variable scale, in the following form.

$$\begin{cases} Minimize\theta \\ Subject \\ to - \sum_{j=1}^{n} x_y \lambda_j \lambda + \theta x_{ik} \geq 0 \\ \sum_{j=1}^{n} y_{rj} \lambda_j \geq y_{rk} \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \geq 0 and \theta : unrestricted \end{cases} \quad (1)$$

The bank efficiency derived by the CCR method is a technical efficiency with constant scale payoffs, but in reality, every bank cannot produce at constant scale payoffs, so the scale efficiency cannot be observed in the calculation results, so the efficiency under the BCC model, which decomposes the technical efficiency into pure technical efficiency (PTE) and scale efficiency (SE), is used to evaluate the bank efficiency. appears to be more reasonable. In this way, the pure technical efficiency indicator measures the bank's efficiency status without considering the influence of scale factors, i.e., the efficiency determined by the bank's management and operational technology level, while the scale efficiency measures the bank's economy of scale.

3.1.3. Establishment of the index system

The choice of input and output variables in the DEA efficiency evaluation of commercial banks has long been a point of debate. On the one hand, banks provide services rather than easily identifiable physical products, and on the other hand, there is no consistent standard for measuring bank outputs. In order to select input and output indicators for DEA efficiency evaluation of commercial banks, this paper adopts the following three steps.

Step 1: A statistical regression analysis was conducted to identify the factors affecting cash flow as well as market value of commercial banks, using cash flow as the dependent variable and other balance sheet items as independent variables.

Step 2: Perform statistical tests. The t-statistic test is first performed to show the factors influencing cash flow in commercial banks; then the D-W test is performed to show that the factors influencing cash flow are not serially correlated at all.

The correlation table is shown in Figure 1 below.

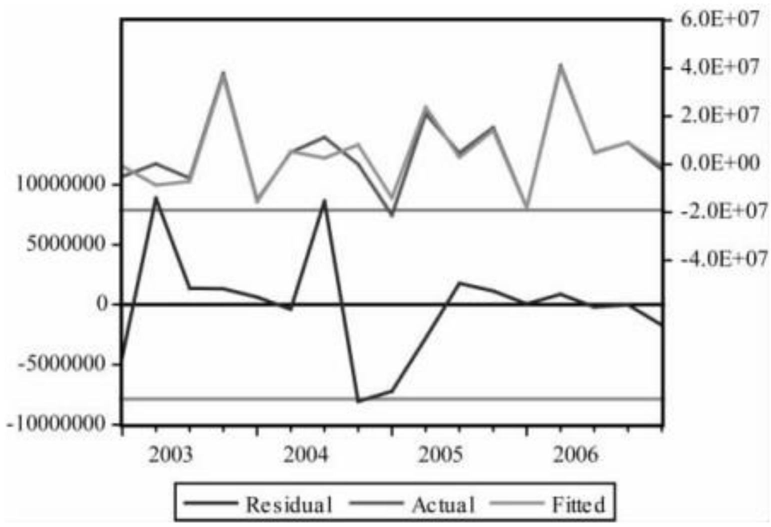

Figure 1. Residual plots

Step 3: Determine the input and output indicators. The indicators determined by the above methods were analyzed by covariance, and the final input and output indicators are shown in Table 2 below.

Table 2. Graphs of covariance analysis

1	0.330549	−0.3215	0.108868	0.157248	0.102232	−0.05359
0.330549	1	0.181642	−0.09749	0.280993	−0.37701	0.238937
−0.3215	0.181642	1	−0.00017	0.608817	0.131621	0.19933
0.108868	−0.09749	−0.00017	1	−0.15369	−0.13695	−0.12437
0.157248	0.280993	0.608817	−0.15369	1	0.591068	−0.01526
0.102232	−0.37701	0.131621	−0.13695	0.591068	1	−0.34093
−0.05359	0.238937	0.19933	−0.12437	−0.01526	−0.34093	1

In summary, this paper identifies the indicators of inputs and outputs in the DEA model: inputs include fixed assets, other assets, wages and benefits; outputs include operations, deposits, deposits with interbank and other financial companies, and deposits from interbank and other financial companies.

3.1.4. Collapse demarcation line

Import of the header data into the calculation yields the collapse line value as shown in Table 3 below.

Table 3. Table of collapse cut-offs

Symbols	Specific meaning	Failed Institutions	Normal operating institutions
X1	Interest income/earning assets	9.364111	14.39266
X2	Net interest income/earnings assets	5.38121	10.57424
X3	Profitability on Assets (ROA)	-3.88139	9.084073
X4	ROE	-102.991	50.91689
X5	Retained earnings/equity	-103.337	21.04438
X6	Net write-offs/loans	3.934029	3.10738
X7	Income before taxes/net write-offs	3.7532	67.7585
X8	Assets per capita	2.26808	12.25632
X9	Allowance for loan losses/loans	4.132388	3.793556
X10	Allowance for loan losses/non-performing loans	77.52881	421.8934
X11	Non-performing loan ratio	11.23328	1.980235
X12	Capital Adequacy Ratio	3.185237	24.49854
X13	Core Capital Adequacy Ratio	3.201603	24.56782

Its consistency test:

Generally speaking, the 13 indicators mentioned above must pass the mean test, and only those indicators that show significant differences between failed and healthy banks are selected for inclusion in the model. In SPSS software, testing whether there is a significant difference in the mean values is generally performed by assessing the Wilks Lambda test volume. The results of the mean tests for the 13 indicators mentioned above are are shown in Table 4 below.

Table 4. Results of the mean test of the selected indexes

	Wilks' Lambda	F	df1	df2	Sig.
X_1	.879	18.802	1	137	.000
X_2	.869	20.656	1	137	.000
X_3	.506	133.988	1	137	.000
X_4	.343	262.399	1	137	.000
X_5	.547	113.318	1	137	.000
X_6	.988	1.690	1	137	.196
X_7	.983	2.365	1	137	.126
X_8	.993	1.018	1	137	.315
X_9	.998	.329	1	137	.567
X_{10}	.970	4.202	1	137	.042
X_{11}	.544	114.962	1	137	.000
X_{12}	.788	36.858	1	137	.000
X_{13}	.807	32.743	1	137	.000

As can be seen from the above table, at the 0.01 level of significance, we reject the hypothesis that the variables X1, X2, X3, X4, X5, X11, X12, X13 have equal means in the two groups, i.e., we consider that the means of the above indicators are significantly different in the two groups of failed banks and healthy banks. The above eight indicators passed the primary selection into the model.

3.2. Find the most important 5 metrics data

3.2.1. Model building and solving - SFA model based on principal components [2-5]

Let ynt denote the net bank interest income of the nth bank in period t, and P1nt..., Pknt denote the values of the principal components. Establish a stochastic efficient frontier (SFA) model based on principal components as

$$lny_{nt} = c + \beta_1 p_{1nt} + \cdots + \beta_k p_{knt} + v_{nt} - u_{nt} \tag{2}$$

Where c is the intercept term, β_1, ...,β_k are the coefficients.v_{nt} ' is a random error term with zero mean and finite variance, denoting other factors not considered in the model, andu_{nt} is the technical inefficiency term.

The SFA model suggests that the factors affecting the efficiency of banks' output include three components. One is the technical inefficiency term that is not considered in the model and negatively affects the net interest income of the banku_{nt} The second is the random factor nt that has a stochastic shock on the bank's net interest income, and the third is the effect of the input variables represented by the principal components on the net interest income. The effect of each principal component on net interest income is given by the coefficient β1,...... ,β_k denoted.

Based on the technical inefficiency termu_{nt} The time-varying assumption sets the variation of the technical inefficiency term in the form of

$$u_{nt} = exp(\eta(t - T))u_n \tag{3}$$

1) t-test of SFA model coefficients
2) LR test of SFA model coefficients
3) Gamma coefficient test for SFA model setting
4) t-test of the time-varying technical efficiency coefficient n

3.2.2. Specific calculations

Column 2 of Table 1 shows the results for the correlation coefficient ρ. Column 3 shows the corresponding concomitant probabilities p. Column 4 gives the test conclusions. Column 4 of Table 5 shows that interest expense, total deposits, loan balance, fixed assets, total assets, and number of employees are significantly correlated with net interest income. So, there is a significant effect on net interest income using principal components extracted from input variables such as interest expense, total deposits, loan balance, fixed assets, and total assets. The characteristic roots, variance contributions and cumulative variance contributions are calculated as shown in Table 6 below.

Table 5. Correlation coefficient test between input variables and net interest income

Serial number	(1) Variables	(2) ρ results	(3) The probability p	(4) Remarks
1	Interest Expense (lnx1)	P=0.880	P=0.000	Significant
2	Total deposits (lnx2)	P=0.906	p=0.000	Significant
3	Loan balance (lnx3)	P=0.889	p=0.000	Significant
4	Fixed assets (lnx4)	P=0.816	p=0.000	Significant
5	Total assets (lnx5)	P=0.909	p=0.000	Significant

Table 6. Calculation results of characteristic roots, variance contribution and cumulative variance contribution

Serial number	(1) Principal components	(2) Characteristic roots	(3) Contribution of variancebi (%)	(4) Cumulative variance contribution rate vk (%)
1	1st principal component	$\lambda 1 = 5.326$	b1 =88.772	v1 =88.772
2	2nd principal component	$\lambda 2 = 0.413$	b2 =6.886	v2 =95.658
3	3rd principal component	$\lambda 3 = 0.132$	b3 =2.194	v3 =97.852
4	4th principal component	$\lambda 4 = 0.082$	b4 =1.362	v4 =99.214
5	5th principal component	$\lambda 5 = 0.033$	b5 =0.558	v5 =99.772

Their respective weights are as follows.

Z=0.012X1 +0.014X2 +0.033X3 +0.006X4 +0.999X5

3.3. proposes a failure risk prediction model

3.3.1. Comparative results analysis of the previous paper

Comparing the above shows that the benefits of the principal component-SFA-based bank input-output efficiency evaluation model are twofold.

First, the SFA model is built using uncorrelated principal components, which reduces the number of independent variables and thus increases the degrees of freedom of the model. Since the principal components are not correlated with each other, the SFA model solves the problem of multiple coefficients caused by the correlation between the input variables and makes the estimated SFA model coefficients statistically significant. In contrast, the SFA model based on input variables, due to the large number of variables and the high correlation between input variables, leads to insignificant coefficients for total deposits, fixed assets and total assets in the model.

Second, using principal component regression, which reflects the relationship between principal components and input variables, and then building a bank input-output model, the obtained parameter signs of input variables are positive, which is in line with theoretical expectations. In contrast, the SFA model based on input variables, due to the large number of variables and the high correlation between input variables, leads to a negative coefficient of the model fixed assets, which is not in line with economic theory.

3.3.2. Collapse risk prediction model

Fisher's discriminations [6-8]

By applying different discriminant rules, different discriminant functions can be solved. The commonly used discriminant rules are distance discriminant, Bayes discriminant and Fisher discriminant. Among them, Fisher's discriminant is the most widely used.

Fisher discriminant is solved for the discriminant function U(x) according to the rule that the within-group variance is as small as possible and the between-group variance is as large as possible.

(1) Statistical significance

After the discriminant model has been computed, its significance must be evaluated. There are a number of different statistical criteria that can be applied; Wilk's lamada, Hotelling's trace and Pillai's criterion can all be used to evaluate the significance of the discriminant validity of the discriminant function.

(2) Evaluation of the overall fit

A. Calculate the discriminant Z score

According to the obtained discriminant function (1.2.1), etc., the Z discriminant score for each sample is obtained by substituting each financial data X of the sample into the 1.2.1) equation.

B. Determine the critical value Z for the discriminant Z score.

After getting the discriminant Z score for a certain sample, how to interpret this score? What value of the score represents collapse or survival? Usually, we have to determine the critical value Z of the Z discriminant score.

If the two groups have the same number of samples, then

$$Z_0 = \frac{1}{2}(Z_A + Z_B) \tag{4}$$

Where ZA is the mean discriminant Z score for group A and ZB is the mean discriminant Z score for group B.

If the sample size of each group is unequal, then

$$Z_0 = \frac{N_A Z_A + N_B Z_B}{N_A + N_B} \tag{5}$$

Where N. and N are the sample sizes of groups A and B.

Once the Z-value is obtained, the Z-score obtained for each sample can be compared with the Z. value. If the Z score of a sample is greater than Z. then it should be classified as healthy; otherwise, it will be classified as failing.

C. Determine the classification table - prediction accuracy evaluation

In discriminant analysis, each observation is evaluated by whether it is correctly categorized or not. For each sample, its Z discriminant score is calculated and compared with Z. The predicted result is then compared with the actual condition in four cases.

Scenario a is actually failing and Z<Z. predicted by the model; Scenario b is actually failing and Z>Z. predicted by the model; Scenario c is actually healthy and Z<Z. predicted by the model; Scenario d is actually healthy and Z>Z. predicted by the model.

In both scenarios b and c, the opposite of the prediction and the actual situation indicates a forecast error. Usually, in bank failure warning studies, scenario b, in which an otherwise failing institution is incorrectly predicted to be a healthy institution, is referred to as the first type of error, while scenario c, in which an otherwise healthy institution is incorrectly predicted to be a failing institution, is referred to as the second type of error.

Let the number of observations corresponding to the above four cases be A, B, C and D (A ten B + C ten D = N, N represents the total number of observations), then we have.

Type I error rate = B/(A+B), Type II error rate = C/(C+D) Accuracy rate = (A+D)/N

Generally, we measure the accuracy of the early warning model by the first type of error rate, the second type of error rate and the accuracy rate mentioned above. The following classification table7 is usually used to represent the above prediction results.

Table 7. Threshold valuesZ_0 Classification Table

Threshold value Z0		
Actual	Projections	
	Closure	Survival
Closure	A	B
Survival	C	D
Type I Error Rate	B/N	
Type II Error Rate	C/N	

D. Model warning

For the test samples, the same classification table can be given as in step (3) to obtain their classification accuracy and first category error rate, second category error rate and accuracy rate.

3.4. Screening of representative banks to forecast the risk of failure of other banks

Hierarchical Analysis (AHP)

In fuzzy hierarchical analysis [9-10], the two-by-two comparison judgment between factors is expressed quantitatively using the importance of one factor over another, then the fuzzy judgment matrix A (aij) nn is obtained if it has the following properties.

(1) aij = 0.5, i = 1, 2,..., n

(2) aij+ aji =1, i = 1, 2,..., n

Then such a judgment matrix is called the fuzzy complementary judgment matrix. In order to obtain a quantitative description of the relative importance of any two solutions with respect to a criterion, a quantitative scale is usually given by the 0.1 to 0.9 scale method as in Table 8.

Table 8. Meaning of scales

Scale	Definition	Description
0.5	Comparison of the two elements	Comparison of two elements of equal importance
0.6	Comparison of the two elements	One element is slightly more important than the other
0.7	Comparison of the two elements	One element is significantly more important than the other
0.8	Comparison of the two elements	One element is much more important than the other
0.9	Comparison of the two elements	The extreme importance of one element over another

aii = 0.5 indicates that the factor is equally important compared to itself; if aij 0.1, 0.5), then factor xj is more important than xi; if aij (0.5, 0.9), then factor xi is more important than xj.

Based on the five indicators filtered in question 2, into which we substituted, for the selection calculation, the

The 2017 data contains 7,027 instances (financial statements), 271 representing insolvent companies and 6,756 companies that were not insolvent during the forecast period.

It is possible to get there are 20 existing banks.

Other Bank Failure Risks Forecast

Assuming that banks that are directly or indirectly connected to each other constitute a banking system, this connection among banks provides conditions for the occurrence of bank risk contagion. To obtain the differential equation satisfied by p(t), similar to the assumptions of the Levies model in the pooled population, we build a bank risk contagion model and assume "18: 1) assume that the environment of bank risk contagion is in a range that can satisfy its risk contagion conditions 2) assume that the bank risk contagion process has a constant contagion rate c and extinction rate e (c, e have the same meaning as above); 3) assume that the contagion rate is always greater than the extinction rate in the bank risk contagion process, i.e., c > e is constant.

Based on the above assumptions, the proportion of banks exposed to risk contagion at moment t satisfies.

$$\begin{cases} \frac{dp(t)}{dt} = cp(t)(1-p(t)) - ep(t) \\ p(0) = p_0 \end{cases} \tag{6}$$

Dynamic simulation of bank risk contagion using metacellular automata with the help of Matlab software.

A tuple, also known as a cell or primitive, is the most basic component of a tuple automaton, and its state can be set as desired. In this paper, we consider a single bank in the study area as a tuple, which corresponds to two states of contaminated and uncontaminated risk. The set of spatial outlets in which the tuple is distributed constitutes the tuple space. The tuple space is infinitely extensible in all dimensions, and in order to achieve this ideal condition on the computer, we define different boundary conditions: periodic, reflective and fixed-value.

In this paper, we use a periodic type of boundary condition, which refers to the metacell space connected by relative boundaries. For a one-dimensional space metacellular space behaves as a first and last circle, and for a two-dimensional space, it forms a topological circular surface similar to a car tire. Periodic space is closest to infinite space, and thus such space type is often used as a condition for boundary satisfaction in theoretical discussions. Together with the evolutionary rules, the dynamic component is introduced into the system. In a metacellular automaton, these rules are defined in the local scope of space, i.e., the state of a cell at the next moment is determined by its own state and the state of its neighboring cells. Therefore, before formulating rules, it is necessary to define the progenitor rules and specify which cells belong to the progenitor of the cell, which is necessary for the dynamic evolution of the cell. In this paper, we select 100×100 banks in a region, and adopt von Neumann's proton structure. The selected contagion nodes (the number of banks with contagion at the initial moment) are single-point contagion, 2-point contagion and 3-point contagion, and the time steps are 10, 50 and 100 involving 200 steps respectively for the comparison of the spatial distribution of bank risk contagion. The coordinates of the contagion points for single-point contagion are chosen as (25, 25), for 2-point contagion are chosen as (30, 30) and (70, 70), and for 3-point contagion are chosen as (30, 50), (50, 30) and (80, 80). If the initial moment of vulnerability is one, two and three banks, and the time steps are 10, 50 and 100 and 200, figure 2 below shows the dynamics of the contagion of the banks in the region in time and space are demonstrated. The white and black colors indicate the contaminated and non-contaminated banks, respectively.

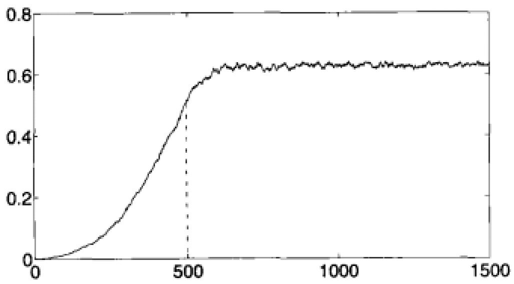

Figure 2. Time-space dynamic demonstration process

The analysis shows that it is basically in line with the five-year trend in the number of failed banks given by the question.

3.5. Predicting Bank Failure Trends Using Fuzzy Cluster Analysis

For which data may come from the same bank, here we use fuzzy cluster analysis method.

Fuzzy clustering analysis

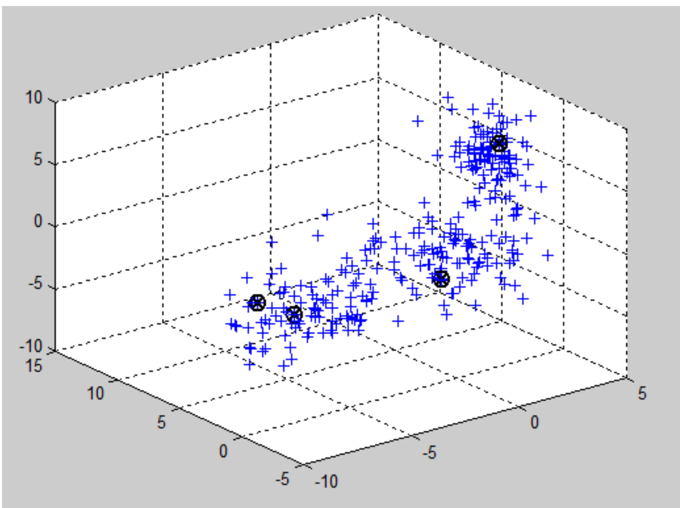

Figure 3. Initial clustering analysis

For the maximum fuzzy support tree in fuzzy cluster analysis [11-12], different classification results can be obtained when λ = 1, λ = 0.9, λ = 0.8, λ = 0.7, and λ = 0.4 are chosen, respectively, and a cluster spectrum graph can be obtained by this process as shown in Figure 3 and Figure 4 below.

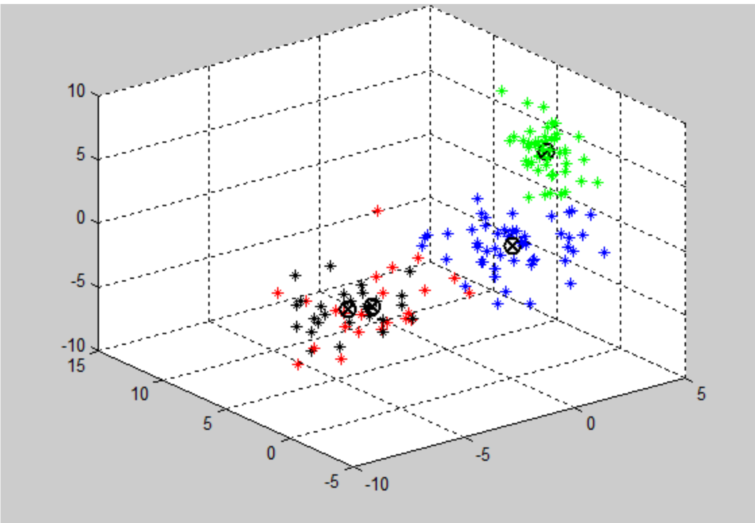

Figure 4. Final clustering center

Closing trends.

The calculation yields 410 banks with a large trend of failure.

4. Conclusion

As the trend of global economic integration intensifies, the challenges facing the financial sector are becoming more apparent. Many banks have become indebted or even insolvent due to the proliferation of non-performing loans and bad debts, so it is crucial to evaluate the efficiency and analyze the bankruptcy of banks in other countries in order to avoid losses to the national economy. This paper focuses on establishing a reasonable efficiency evaluation system and failure risk assessment prediction model for banks and further analyzing the causes of bankruptcy.

The model built in this paper, based on the data given in the annex, has been comprehensively preprocessed, including data integrity analysis, variable and data analysis and processing, etc., which has laid a good foundation for the correct use of the data; a number of factors and data have been considered comprehensively, after a systematic theoretical analysis, and the algorithm is stable and the calculation results are more accurate. However, there are also some shortcomings in the proposed model. The accuracy of the model built in this paper will be significantly reduced when there are large changes in national policies and force majeure such as natural disasters, based on which the model can continue to be optimized with consideration of national policies and markets. In summary, the bank efficiency evaluation and bankruptcy analysis model we have given in this paper, the specific evaluation scheme, etc., when put into use in real life, together with the comprehensive consideration of other factors in reality, can provide a good reference for bank management and enterprise management, and can be extended to more regions to help solve ecological environment problems.

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