Research for MSMEs Credit Strategy Based on RFM Model

Guan Li, Jianming Chen, and Xinxin Huang(✉)

Guangdong University of Science and Technology, Dongguan 523083, Guangdong, China
huangxinxin@gdust.edu.cn

Abstract. The small size of MSMEs and the lack of collateralizable assets make it difficult for banks to reliably classify the credit ratings of MSMEs. This paper constructs an RFM model to accurately classify the credit rating of MSMEs, extracts the behavioural characteristics of enterprises, and uses the K-means clustering algorithm to subdivide the credit rating of enterprises, ultimately realising the classification of MSMEs with different credit ratings. From the perspective of bank profit and risk control, differentiated credit strategies are formulated for different credit grades of MSMEs to maximise the overall bank profit.

Keywords: credit strategy · quantitative analysis · RFM model · K-means algorithm

1 Introduction

MSMEs are an important part of China's economic system and play an important role in promoting national economic development. However, credit problems for MSMEs have always existed, for example, credit is difficult, credit is expensive and credit cycles are long. In recent years, studies have found that small scale, poor risk resistance and low income per household are the main reasons for the credit problems of MSMEs [1, 2] in the development process. At the same time, Chinese banks are not sufficiently risk-aware, the credit rating system is not perfect, the credit risk transfer market is not perfect, the concept of risk prevention and control is lagging behind, and the prevention and control methods are backward. From the bank's perspective, the traditional credit business of banks can hardly meet the "short, small, frequent, fast and urgent" credit needs of MSMEs, and there are also huge risks [3].

The credit default rate of an enterprise is used to determine its ability to repay, profitability and sustainability [4–6]. Banks extend credit to MSMEs to try to maintain the safety of the principal, and therefore need to decide their credit strategy for the enterprises based on the default rate of MSMEs [7, 8].

The design of this paper is based on data from 123 MSMEs with credit records, such as bank profits, enterprise delinquency rates, enterprise inputs and outputs, etc. A constrained linear programming problem is constructed to build the RFM model. By extracting the behavioural features of the RFM and using the K-means algorithm to cluster and stratify the 302 MSMEs without credit records, the credit classes are

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classified and the optimal credit strategy of the bank for each type of enterprise with a fixed annual credit limit is obtained.

2 Building the RFM Model

The data required for this paper were obtained from the data of the 2020 National Student Mathematical Modelling Competition, including statistical data on input and output invoice information, enterprise type, credit rating and the relationship between the enterprise's loan interest rate and customer churn rate for a total of 425 micro and small enterprises with credit records and 302 without credit records from 2017 to 2020.

The model is based on the following conditions: Assumption 1: Absolute accuracy of the data relating to the credit records of each enterprise; Assumption 2: Indirect effects of various unintended factors on the enterprise are not considered; and Assumption 3: Effects on unexpected factors, where the effects on other factors (such as the ability of the enterprise to self-manage, etc.) are measured using a uniform standard.

The RFM model is an important tool and instrument for measuring customer value and the customer's ability to generate profit. In the RFM model, R stands for proximity (time of customer activity), F stands for frequency (frequency of customer transactions) and M stands for amount (amount of money purchased by the customer.) The RFM model can describe the value status of a customer through the behavioural characteristics of the customer. The RFM model can dynamically present the full profile of the customer and provide the basis for personalised communication and service. It can accurately determine the long-term value of a customer and support more marketing decisions.

2.1 Constructing Constrained Linear Programming Problems

Assume that banks are social economies that aim to maximise profits and that they have a total fixed credit line of \$100 million for MSMEs for the year. Under the condition that the total fixed credit line is \$100 million, the maximum profit can be obtained by giving different interest rates and loan amounts to different credit classes of MSMEs. Therefore, it can be mathematically considered as a linear programming problem with constraints. The constraint is constructed as follows.

Based on the credit rating, banks can classify MSMEs into four categories, A, B, C and D. Since all enterprises in category D are overdue and are not allowed to lend, it is assumed that only enterprises in categories A, B and C need to be analysed when the total amount of bank credit is fixed at 100 million yuan per year (Table 1).

Binding conditions:

$$n_A(1-f_A)y_A + n_B(1-f_B)y_B + n_C(1-f_C)y_C = 100\ million \tag{1}$$

$$y_A > y_B > y_C, r_A < r_B < r_c \tag{2}$$

Bank profits:

$$W = n_A(1-f_A)y_A r_A + n_B(1-f_B)y_B r_B(1-e_B) + n_C(1-f_C)y_C r_c(1-e_C) - n_A y_A 4\% \tag{3}$$

Table 1. Classification of the different classes of enterprises

Corporate level	*Credit limit(y)*	*Loan Rates(r)*	*Number of companies applying for lending(n)*
A	y_A	r_A	n_A
B	y_B	r_B	n_B
C	y_C	r_C	n_C

1) Where, $f_{A,}, f_B, f_C$ is the customer churn rate for different levels of businesses.

The overdue rates of different classes of companies can be obtained from the overdue information of 123 companies.

$$Overdue\ Rate: e_B = \frac{m_B}{n_B} \tag{4}$$

where, m_B is the number of defaulting firms in Type B, $e_C = \frac{m_C}{n_C}$, of which m_C is the number of defaulting firms in type C.

2) Risk-free returns from the bank for maximum protection of interests.

If all of the profit is lent to firm A at 4%, Eq. (5) is obtained:

$$\mathrm{w} = n_A y_A 4\% \tag{5}$$

2.2 RFM Modeling

The projection of 302 MSMEs without a credit rating requires a survey of 123 MSMEs with a credit history. The strength of an enterprise can be judged by the total amount of inputs and outputs and the number of buyers for each enterprise. The larger the transaction amount and the greater the number of buyers, the stronger the enterprise. In order to determine whether the supply and demand of an enterprise is stable, the total amount of input and sales of different enterprises in a given year and month can be counted and the average, maximum and minimum values of the amount of input and sales can be calculated. The code of the purchasing unit gives an idea of the influence of the enterprise on the upstream and downstream enterprises.

1) Behavioural feature extraction for RFM models.

The invoice data provided by MSMEs is a large volume of input and output data over a period of time, which makes it difficult to intuitively obtain decision making information to differentiate the creditworthiness of an enterprise. Therefore, this paper uses the RFM feature extraction method to extract the input and output data of invoices.

R: Duration of the latest invoicing interval (Recent)

F: Invoicing frequency (Frequency)

M: Invoiced input amount, tax amount, total price and tax amount, output amount, tax amount, total price and tax amount (Monetary)

Using the Python data analysis tool, the statistical analysis was carried out on the input amount, tax amount, total price tax amount, output amount, tax amount, total price tax amount of 123 MSMEs with credit records. The monotonicity of the above statistics is not affected by the logarithmic treatment due to the large variation in the data. According to the logarithmic box plot of the total price and tax amounts, the higher the credit rating, the greater the logarithm of the total price and tax amounts and the greater the total price and tax amounts.

2) Clustering and stratification of customer classes based on K-means algorithm. Based on the behavioural characteristics of RMFs, the total input tax invoice price and tax, total output tax price and tax, the number of upstream and downstream cooperative enterprises, the number of input and output invoices provided, and the input invoice invoicing time interval were constructed for each MSME. The K-means algorithm uses a dynamic clustering algorithm to classify 302 MSMEs with no credit history into four credit classes - A, B, C and D. The K-means algorithm requires the prior determination of the number of clusters K and a sample set $\{x_1, x_2 \cdots\cdots x_n\}$ containing n sample points, and the random selection of K samples $\{m_1, m_2 \cdots\cdots m_k\}$ from the n samples as the initial cluster centres.

For each sample point x_i, $i = 1, 2 \cdots n$, calculate the distance $k = 1, 2 \cdots k$, between each sample point and m_k, and place the nearest sample point into the corresponding class set C_x. For each C_k $(k = 1, 2 \cdots k)$, the mean of each class is calculated as its class centre, $m_k = |C_k|$. Then, the distance between, each sample and the recalculated k clustering centres is recalculated and the process continues until the clustering centres no longer change. The mathematical expression for this definition is shown in below.

$$E(x_i, \ldots, m_M) = \sum\nolimits_{i=1}^{N} \sum\nolimits_{k=1}^{M} I(x_i \in C_k)||x_i - m_k||^2 \tag{6}$$

where x_i denotes the ith sample of the input, m_k denotes the class centre of the Kth class, C_k denotes the set of samples belonging to the Kth class, i.e. the sample points belonging to the Kth class, and E denotes the Euclidean distance sum of squares of each sample point to its corresponding class centre.

As the KMEANS clustering algorithm is susceptible to extreme values, the results of the credit rating ratings of 302 MSMEs and the mean values of the characteristics can be obtained by multiple clustering and RFM feature analysis.

3 Research Results and Analysis

3.1 Conclusions on Constructing Constrained Linear Programming Problems

A quantitative analysis of data from 123 MSMEs with credit records led to the conclusion that the default rate and fruit of 123 enterprises with credit records (Table 2). From Table 1, it can be seen that Category A enterprises have no default records, while Category D enterprises are all overdue and therefore credit is cancelled for Category D enterprises. Looking at the number of 123 enterprises with credit records, the ratio of 4 types of rated enterprises basically satisfies 2:3:3:2.

The higher the credit rating of a business, the lower the default rate and the lower the risk to the bank; therefore, if the bank lends all its money to a Category A business at 4%, it can guarantee a risk-free underlying profit value for the bank. The higher the interest rate at which a bank lends, the higher the rate of customer churn. At the same

Table 2. Overdue default rates for different classes of business

	Whether in default			
Credit rating	**No**	**Yes**	**Overdue Rate**	**Percentage of**
A	27	0	0.0%	22.0%
B	37	1	2.6%	30.9%
C	32	2	5.9%	27.6%
D	0	24	100.0%	19.5%
Total	96	27	22.0%	100.0%

Table 3. Credit line results for 123 firms with credit records

	Loan interest rate			***Line of credit (Ten thousand)***			
Credit limit difference (Ten thousand)	***Grade A***	***Grade B***	***Grade C***	***Grade A***	***Grade B***	***Grade C***	***Total profit (Ten thousand)***
5	0.1025	0.1185	0.1265	95	90	80	560
10	0.0985	0.1185	0.1225	95	85	75	547
20	0.1025	0.1065	0.1105	95	75	55	517

lending rate, the churn rate is greater for firms with a high credit rating than for firms with a low credit rating, i.e. when the bank lending rate is lower, there is less risk. Churn is lower for firms with low credit ratings when bank lending rates are higher, i.e. firms with poor credit ratings are willing to pay more interest to obtain a bank loan. Firms with high credit ratings have a higher churn rate and are more risky.

The constrained linear programming problem constructed gives the following results: The greater the difference in credit limits between the different ratings, the lower the profitability. When the credit line difference is $50,000, the maximum profit is approximately $5.6 million (see Table 3), minus $2 million in costs, which still results in a profit of $3.6 million (Table 3).

3.2 Analysis of the Findings Based on the RFM Model

Behavioural feature extraction based on RFM model, box line plot, scatter plot using python quantitative analysis tool. Capturing the distribution characteristics of 123 MSMEs with credit records through box line plots (A, B, C and D in the box line plots represent MSMEs of different credit grades).

Figure 1 shows the box line plot of the logarithm of the total input tax price and tax for enterprises in different credit classes. It can be seen from the plot that the higher the credit class of an enterprise, the larger the logarithm of the corresponding input tax

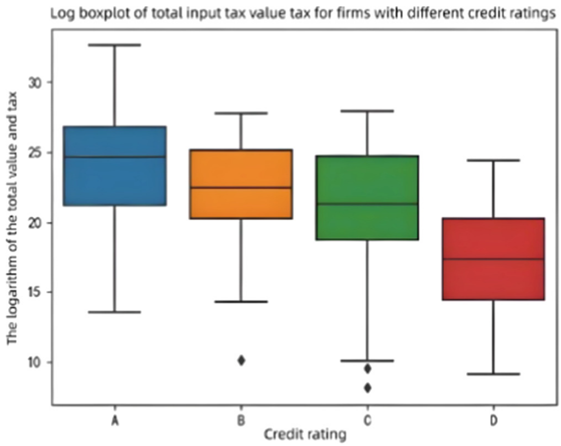

Fig. 1. Logarithmic boxplot of total input tax value tax for enterprises of different credit levels

amount and the total tax amount, and the larger the total input tax amount. The 50% quantile of class A enterprises is basically the same as the 75% quantile of class C enterprises. The 25% quantile of class B companies is basically the same as the 75% quantile of class D companies.

Figure 2 shows a box line plot of the logarithm of the combined sales tax valuation for enterprises with different credit ratings. It can be seen from the figure that when the credit rating of an enterprise is lower, the smaller the logarithm of the corresponding combined sales tax valuation, the smaller the combined sales tax valuation. The 25% quantile for enterprises in category A is basically the same as the 75% quantile for enterprises in category C. the 25% quantile for enterprises in category B is basically the same as the maximum value for enterprises in category D.

Figure 3 shows a box plot of the logarithm of the daily combined sales price tax amount for enterprises with different credit ratings. As can be seen from the graph, the higher the credit rating of an enterprise, the greater the logarithm of the daily combined sales price tax amount and the greater the daily combined sales price tax amount. The 25% quantile for enterprises in category A is essentially the same as the 75% quantile for enterprises in category C. the 25% quantile for enterprises in category B is essentially the same as the maximum value for enterprises in category D.

A box line plot of 123 MSMEs with credit records concludes that the higher the credit rating of an enterprise, the larger the corresponding combined input tax valuation amount. The higher the credit rating of an enterprise, the larger the corresponding combined output tax valuation amount, and the larger the daily output tax valuation amount, the better the economic situation of the enterprise.

The scatter plot captures the hidden relationship between the various characteristics of each type of enterprise and obtains the objective influence of the credit rating of each type of enterprise on the total amount of tax valuation tax (A, B, C and D in the scatter plot represent MSMEs with different credit ratings).

Figure 4 shows the relationship between the total number of sales invoices and the total number of input invoices for enterprises of different credit grades. It can be seen

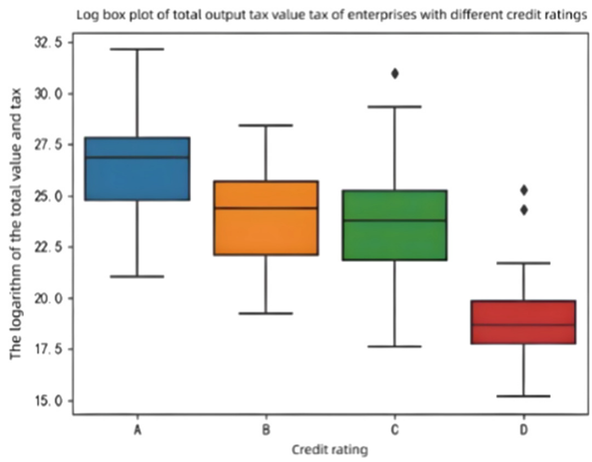

Fig. 2. Logarithmic boxplot of total output tax and price tax for enterprises of different credit levels

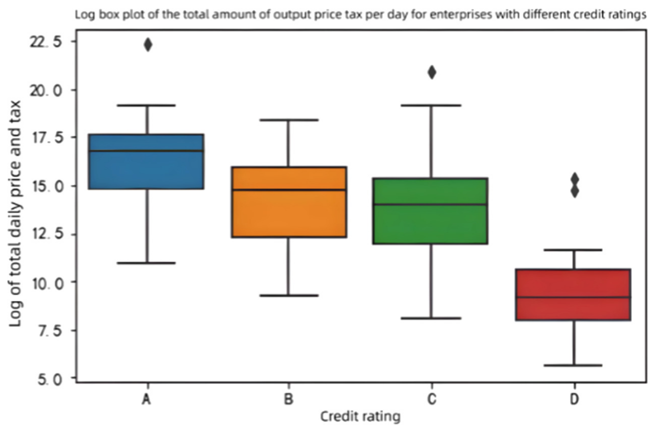

Fig. 3. Logarithmic boxplot of the total amount of output tax and price tax per day for enterprises of different credit levels

from the figure that the higher the credit grade of an enterprise, the higher the total number of input and output invoices. The total number of input and output invoices for enterprises of category A is basically above 5,000, the total number of incoming and outgoing invoices for enterprises of category B is basically below 5,000, and the total number of input and output invoices for enterprises of category D is very small.

Figure 5 shows the scatter plot of the number of purchaser enterprises and the number of seller enterprises for enterprises with different credit grades. It can be seen from the figure that when the credit grade of an enterprise is higher, the more the number of purchaser enterprises and seller enterprises, and the number of purchaser enterprises is basically smaller than the number of seller enterprises. For enterprises with a credit rating of C, the number of purchaser enterprises is basically greater than the number of

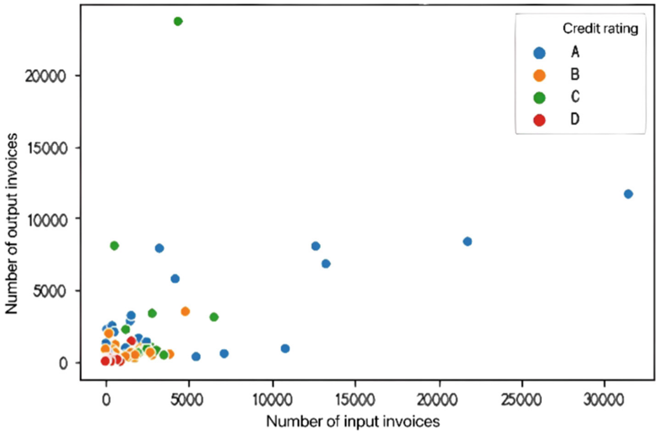

Fig. 4. The total number of sales invoices and the total number of incoming invoices of enterprises with different credit levels

seller enterprises, while for enterprises with a credit rating of D, the number of purchaser enterprises and seller enterprises is relatively small.

Figure 6 shows the relationship between the number of days of sales invoices and the number of days of input invoices for enterprises with different credit ratings. As can be seen from the figure, the interval between the number of days of sales invoices and the number of days of input invoices is longer when the enterprises have higher credit ratings. The interval between the number of days of sales invoices and the number of days of input invoices for enterprises with a higher credit rating is approximately 1100 and 1200 days, with relatively concentrated data. The interval between days of sales invoices and days of input invoices for companies with a credit rating of C is essentially 1,000 and 1,100 days.

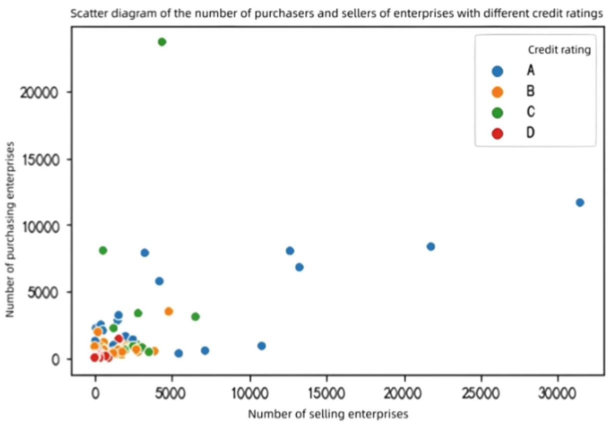

Fig. 5. Scatter chart of the number of buying and selling enterprises of enterprises with different credit levels

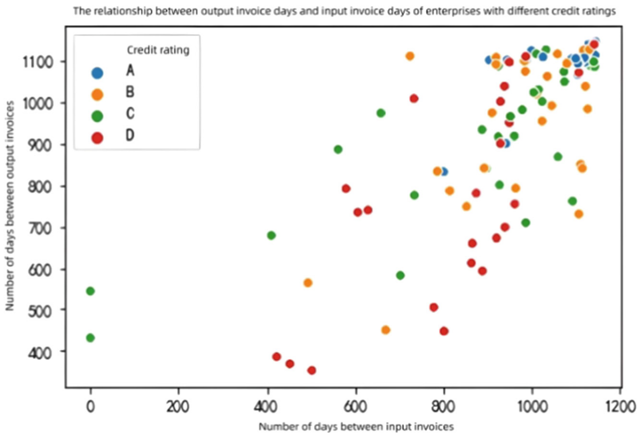

Fig. 6. The number of days of sales invoices and the number of days of incoming invoices of enterprises with different credit levels.

Figure 7 shows the relationship between the daily total amount of price tax on sales and the daily total amount of price tax on inputs for enterprises with different credit ratings. The logarithm of the daily input tax amount is less than 11 and the logarithm of the daily output tax amount is basically less than 11.5.

A scatter plot of the 123 MSMEs with credit records, shows that the higher the credit rating of the enterprise, the higher the number of purchaser enterprises and the number of seller enterprises, and the number of purchaser enterprises is basically smaller than the number of seller enterprises. Enterprises are financially stronger and less likely to have liquidity problems. The higher the credit rating of an enterprise, the longer the interval

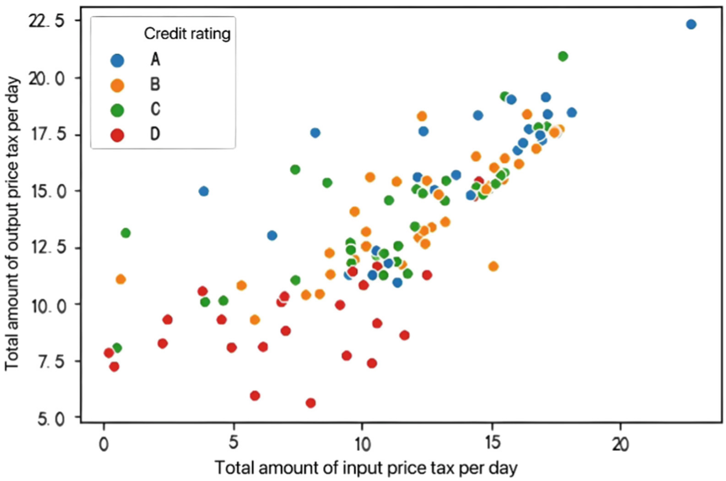

Fig. 7. Graph of the relationship between the total daily output tax price and the total daily input tax price for enterprises of different credit levels.

between the number of days of sales invoices and the number of days of input invoices, indicating that the enterprise has been established for a longer period of time and has a certain economic foundation. Among them, enterprises with credit rating A provide invoice data with a longer time range, can provide historical data for the past three years, and cooperate with more upstream and downstream enterprises, while enterprises in category D basically have the worst of the above characteristics. The differentiation between enterprises in category A and D is very obvious, and the characteristics of enterprises in category B are better than those of enterprises in category C, especially the stability of various data is better than those of enterprises in category C. The higher the credit rating of a business, the greater the combined daily value of inputs and outputs in terms of price and tax, and the greater the combined value of price and tax, the greater the overall transaction value of the business. The higher the credit rating of a business, the greater the total amount of invoices for both input and output, and the greater the number of orders traded.

By capturing the data distribution characteristics of the 123 MSMEs with credit records, the K-means algorithm was used to cluster and stratify the customer classes of the 302 MSMEs without credit records. The first clustering result with a clustering category of 2 is an outlier and belongs to class A based on the characteristics; clustering category 1 and clustering category 3 are very different and are class D and class A respectively. The clustering category is 0, which can be classified as Class B and Class C. A second clustering was performed and the clustering results showed that there were 61 enterprises in category A, 59 in category D and 182 in category B/C (Table 4).

According to the secondary analysis of clustering and RFM characteristics, the number of enterprises in category C was 94 and the number of enterprises in category B was 88. The characteristic values of enterprises in category B were generally better than those of enterprises in category C (Table 5).

Table 4. Clustering of enterprises with credit ratings of A, B, C and D

Class of clusters	0	1	2	3
Number of clustered enterprises	182	59	2	59
Total input price tax	16,406,485	8,321,573	922,702,303	68,972,671
Total output price tax	34,226,785	8,809,789	916,639,429	137,457,656
Number of selling enterprises	638	348	16,520	3,531
Number of purchasing enterprises	563	148	1,240	3,214
The number of days between input invoices	1,009	683	911	1,080
The number of days between output invoices	1,037	688	908	1,083
Number of input invoices	638	348	16,520	3,531
Number of output invoice	563	148	1,240	3,214
Credit rating	B/C	D	A	A

Table 5. Cluster division of enterprises with credit rating B and C

Class of clusters	***0***	***1***	***total***
Number of clustered enterprises	94	88	182
Total input price tax	4,942,970	28,651,603	16,406,485
Total output price tax	8,774,530	61,414,421	34,226,785
Number of selling enterprises	313	984	638
Number of purchasing enterprises	311	833	563
The number of days between input invoices	989	1,031	1,009
The number of days between output invoices	1,025	1,051	1,037
Number of input invoices	313	984	638
Number of output invoice	311	833	563
Credit rating	C	B	

Based on the above clustering results, 302 of the 425 MSMEs with no credit history were classified into enterprise codes of different credit classes (see Table 6), with enterprise codes starting from E 124.

In terms of risk management, the K-means algorithm classified the 302 MSMEs without credit records into four credit classes, A, B, C and D. This yielded: 61 A-rated enterprises, 88 B-rated enterprises, 94 C-rated enterprises and 59 D-rated enterprises, which is largely consistent with the ratio of 2:3:3:2 of A, B, C and D-rated enterprises among the 123 enterprises with credit records. The RFM characteristics for each category are generally consistent with the results for the 123 credit-rated enterprises. Therefore, the clustering results are valid and feasible. Finally, the credit strategy for the 302 firms with no credit history was developed based on a constrained linear programming problem. The A–C loan interest rates were 0.0625, 0.0865 and 0.0905 for a credit line difference of $50,000, and the profit maximum was $7.66 million for credit lines of $950,000, $900,000 and $850,000, respectively (Table 7).

Data analysis shows that an important reason for banks' losses is the high rate of non-performing loans to MSMEs. To truly solve the problem of difficult credit for MSMEs, banks should first improve their risk management capabilities, fully penetrate the risk management process into the credit business of MSMEs, use various means to strengthen supervision and avoid various risks that may occur during operation.

Banks' lending to MSMEs should be geared towards long-term benefits. At present, under interest rate control, the pricing of loans to MSMEs is low and cannot compensate for the risks of MSMEs. If commercial banks choose to lend part of their loans to growth-oriented enterprises and establish good capital and business cooperation with them, they can lay the foundation for higher returns on loans in the future after the marketisation of interest rates.

In addition, financial products and guarantees can be innovated. Where banks can innovate is in diversified microfinance products, micro-lending techniques for small, medium and micro enterprises, etc. It is also important to consider attracting high-quality

Table 6. 302 credit ratings for MSMEs with no credit history

Credit rating	Company code
A	E124 E125 E126 E127 E128 E129 E131 E132 E134 E135 E137 E139 E140 E141 E143E145 E146 E147 E150 E159 E160 E162 E163 E164 E165 E167 E169 E171 E173 E175E176 E177 E180 E181 E188 E189 E191 E193 E194 E195 E196 E197 E204 E206 E207E209 E213 E216 E219 E220 E221 E222 E225 E227 E228 E238 E258 E273 E289 E312 E330
B	E130 E133 E136 E138 E142 E144 E149 E151 E152 E153 E154 E156 E157 E158 E161 E166 E168 E170 E172 E174 E178 E179 E182 E183 E184 E185 E186 E190 E192 E198 E200 E201 E202 E203 E205 E208 E210 E211 E212 E214 E215 E218 E224 E226 E229 E230 E231 E232 E234 E235 E236 E241 E243 E244 E246 E247 E248 E249 E250 E251 E252 E253 E254 E255 E256 E259 E260 E261 E265 E269 E271 E272 E281 E282 E284 E285 E290 E296 E298 E301 E305 E306 E310 E314 E324 E325 E332 E381
C	E245 E257 E262 E263 E266 E268 E270 E275 E276 E277 E278 E279 E280 E283 E287 E288 E291 E292 E293 E294 E295 E299 E300 E302 E303 E304 E307 E308 E309 E313 E315 E316E317 E318 E319 E321 E322 E326 E327 E328 E331 E333 E334 E337 E338 E340 E342 E343 E344 E345 E346 E347 E348 E350 E351 E352 E353 E354 E357 E361 E362 E364 E365 E366E367 E368 E369 E371 E372 E373 E378 E379 E380 E384 E388 E391 E392 E393 E394 E395 E396 E398 E400 E401 E403 E404 E406 E408 E410 E411 E412 E416 E420 E421
D	E148 E155 E187 E199 E217 E223 E233 E237 E239 E240 E242 E264 E267 E274 E286 E297E311 E320 E323 E329 E335 E336 E339 E341 E349 E355 E356 E358 E359 E360 E363 E370 E374 E375 E376 E377 E382 E383 E385 E386 E387 E389 E390 E397 E399 E402 E405 E407 E409 E413 E414 E415 E417 E418 E419 E422 E423 E424 E425

Table 7. Credit line results for 302 firms without credit records

	Loan interest rate			**Line of credit (Ten thousand)**			
Credit limit difference (Ten thousand)	Grade A	Grade B	Grade C	Grade A	Grade B	Grade C	Total profit (Ten thousand)
5	0.0625	0.0865	0.0905	95	90	85	766
10	0.0665	0.0785	0.0825	95	85	75	730
20	0.0585	0.0705	0.0745	95	75	55	651

enterprises to carry out lending operations. We can draw on the experience of foreign banks to innovate financial products that are tailored to the characteristics of MSMEs. Reform the collateral guarantee system in the banking sector and expand the scope of guarantees. For enterprises with good reputation and long-term cooperation, collateral loans can be provided through credit guarantees or corporate guarantees.

4 Conclusion

Although banks have accumulated more mature experience in marketing and managing credit for SMEs over many years of operation, and have established a richer product system and a more comprehensive risk management system, it is still difficult for banks to reasonably distinguish the credit rating of SMEs due to factors such as information asymmetry and rapid changes in the economic environment. This paper uses limited information such as transaction information (invoice information), credit ratings and credit records of real enterprises (123 MSMEs with credit records) to construct a constrained linear problem based on quantitative analysis to measure the indirect relationship between the default rate of such enterprises and the limited information. Then, with the bank's profit maximisation as the objective, the RFM model of the bank's optimal credit strategy is constructed on the basis of extracting the behavioural characteristics of the RFM; the K-means algorithm is used to classify the 302 enterprises (302 micro, small and medium-sized enterprises without credit records) into four credit classes, A, B, C and D. The model is solved under the constraint, so as to obtain the bank's optimal credit for potential customers. The model is solved under the constraints to obtain the optimal credit strategy for potential customers.

The model analyses the factors that influence banks' credit decisions for MSMEs, such as banks' profits, enterprises' overdue rates, and enterprises' input and output data. Taking into account the actual situation of information asymmetry between banks and MSMEs, the limited information such as partial transaction information that banks can access is used for targeted modelling analysis. Through this approach, banks can effectively prevent credit risks to MSMEs while maximising their overall profits.

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