Behavioral Scoring Model for Bank Customers Using Data Envelopment Analysis

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Abstract. This study proposes a behavior scoring model based on data envelopment analysis (DEA) to classify the customers into the high contribution and low contribution customers. Then, the low contribution customers are examined by using the slack analysis of DEA model to promote their contributions. The experiment results showed that the proposed method can provide indeed directions for bank to improve the contribution of the low contribution customers, and facilitates marketing strategy development.

1 Introduction

With more importance attached to risk management, the financial industry now has to take into account the credit risks of contributive customers. Accordingly, to achieve a balance between profit and risk, a customer's contribution is not only considered in terms of expenditure amount or purchase frequency but also the probability of credit risks. Behavioral scoring is a useful tool to assist risk management in the financial industry [1, 2]. Through analysis on the payment history and expenditure records, evaluation can be made on existing customer's credit risk and their consumption habit, so as to assess customer contribution. Behavioral scoring model can be employed for financial institutes to distinguish highly contributive customers from less contributive ones, and its ultimate goal is to reduce loss and increase profit via risk control.

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Nowadays, numerous approaches have been proposed to construct the behavioral scoring model to address relevant issues [3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]. However, most of the existing behavioral scoring models can facilitate discrimination process but not specify directions towards which improvements can be made on customers' performance. Such models can serve as reference on examining whether a customer has good credit, and deserves retaining efforts or whether his and/or her contributes are considerably to the enterprise. They may not be able to analyze less contributive customers, not to provide specific suggestions on marketing or managerial strategies for coping with customers of lower credit score or less contribution. In light of this, this study proposes a customer behavioral scoring model based on data envelopment analysis (DEA). This model is expected to assist banks understanding customer contribution and provide them with directions to improve earnings from less contributive customers.

DEA is an efficiency evaluation model proposed by [15]. As a multi-objective decision-making tool, it analyzes multiple input and output variables of DMUs (decision making unit) to figure out their relative efficiency [16]. Before assessing each DMU's efficiency, DEA dose not presume the relationship between each input and output variable but compares the relative efficiency among DMUs to decide their efficiency value. Also, for inefficient DMUs, specific suggestions can be provided so that the composition of input and output items can be properly adjusted to achieve higher efficiency. DEA has been widely applied to performance evaluation in many fields [17, 18, 19, 20, 21, 22, 23]. Nevertheless, very few studies have been dedicated to the application of DEA in issues related to customer behavioral scoring model.

This study examines the credit card holder database provided by a bank in Taiwan. Each card holder is regarded as a DMU, whose performance is evaluated in a DEA-based behavioral scoring model. Considering the impact of credit risks on banks, customer's payment behaviors (such as whether balance is paid in full each month or revolved) are set as input variables of DEA, while customer's expenditures (such as total amount spent and credit line usage rate) are set as output variables. The purpose of this design is to maximize corporate profit with risks considered. Based on each customer's efficiency score figured out by DEA, efficient customers can be distinguished from inefficient ones. Efficient customers are viewed as high-contribution customers because, in the trade-off relationship between customer's credit risk and bank's revenue, performance of such customers is better and more balanced than inefficient (or low-contribution) ones. Finally, the proposed model is applied to further analyze low-contribution customers, so as to derive appropriate marketing or administrative strategies with an aim of developing personalized marketing and customized management to reduce misuse or abuse of resources and improve customer contribution.

The remainder of this paper is organized as follows. Section 2 reviews literatures about behavioral scoring model and DEA; Session 3 gives a brief introduction to DEA; Session 4 presents a detailed discussion on the empirical results obtained from the proposed behavioral scoring model; Session 5 concludes the study with suggestions for further researches.

2 Data Envelopment Analysis

Based on the concept of replacing "predicted production functions" with "non-predicted production functions", DEA measures the relative efficiency of each DMU. Among various models of DEA hinging on their corresponding assumptions, CCR models, based on constant return to scale, are most often used in literature [19, 20].

The CCR model is a type of non-parameter estimation method that does not require assumption of production function and estimate function parameters. Weights in the model are determined by the input and output factors. And depending on perspectives used, CCR models can be either input-oriented or output-oriented. The input-oriented approach examines the current output level to understand which input method is the most efficient, while the output-oriented method compares the efficiency of different output methods under the same input level. In practice, the analysis approach is usually selected according to the control over either of input and output variables.

3 Empirical Study

This study examined a dataset of 1000 credit card holders (including customer data and credit records) provided by a bank in Taiwan. Each card holder's contribution was measured with the proposed DEA behavioral scoring model, and suggestions were also made on low contribution customers.

Credit risk not only has significant influence on credit granting but also reflects card holder's ability to pay debts. Thus, card holder's payment behavior is taken as an input variable in DEA. Considering data constraints, findings from literature review and expert suggestions, three variables were selected: the worst payment ranking of the month (X1), the worst payment ranking of the last 3 months (X2), and the worst payment ranking of the last 6 months (X3). Each input variable has two categories, namely "pay in full" and "revolve balance". Since DEA processes only numerical data, the two categories have to be coded as 1 and 2 respectively.

The output variables were also selected through literature review and expert interview. Factors that can reflect a card holder's purchasing power and consumption capacity should be used as output variables in DEA, namely "credit line usage rate of the month" (Y1), "average credit line usage rate of the last 3 months" (Y2), "average credit line usage rate of the last 6 months" (Y3), and "expenditure of the month" (Y4). Considering the convenience and practicality of customer management for banks, instead of using actual values, each variable was further divided into 5 categories as suggested by experts to make the analysis results more concise and comprehensive.

Besides, there should be significant and positive correlations between the output and input variables so that the isotropy between the variables and significant interactions between input resources and output performance can be presented. Therefore, correlation analysis was performed on the input and output variables and results shows that they do exhibit strongly positive relationship.

In this study, card holders were clustered via DEA. Those with efficiency value of 1 were considered as high-contribution customers while the rest were viewed as low-contribution ones. After computation, the average efficiency score of all the card holders was 0.558, with a standard deviation of 0.225. Among all the 1000 samples, 128 card holders were rated as high-contribution customers (12.8%) and the remaining 872 card holders were judged as low-contribution customers whose expenditure or payment behavior could be further improved.

Sample ID 561 and 871 are examples of a detailed DEA analysis on the high-contribution customers. Both high-contribution card holders paid the balance in full each month, indicating that they had very low credit risks. In view of the output variables (consumption), their credit line usage rates were 5% - 10% and 10% - 50% respectively, with total expenditure of each month over NT$20,000, implying that their consumption capacities were good. DEA's recommended value was the same as the actual value and there was no need to improve these customers' efficiencies. Hence, from the standpoint of bank, they were regarded to as efficient customers or "high-contribution credit card holders".

Further on the analysis of low-contribution card holders, three examples were employed, including Sample ID 477, 134 and 703. Sample ID 477 had an efficiency value of 0.5, relied on revolving balance in all the three variables for payment behavior, and reached the highest expenditure level. It can be inferred that this customer had very good consumption capacity but also high credit risks. Hence, DEA suggested that, in order to improve this customer's contribution, the emphasis should be put on his/her payment behavior. If the reliance on revolving balance can be replaced by paying balance in full each month, the bank can have one more efficient customer. For this customer, DEA prescribed directed improvements on inputs from the perspective of risk control.

Furthermore, DEA results also indicated that the efficiency value of Sample ID 134 was 0.75 and this customer tended to pay balance in full each month, implying a very low credit risk. However, this customer's consumption should be encouraged. In terms of credit line usage rates of the last 3 months and the last 6 months, the customer performed well and could remain in the current level, yet credit line usage rate of the month should be raised from below 5% to 5% ~ 10%. Moreover, the total expenditure of the month should be increased from below NT$5,000 to the level of NT$20,000 ~ NT$60,000. For this customer, DEA recommended that the output, i.e. consumption of this customer, can be improved.

Finally, the efficiency value of Sample ID 703 was 0.62. DEA gives suggestions on improvements for each card holder in terms of risk management and expenditure. To reduce risk, "payment ranking of the latest 6 months" should move from "revolve balance" to "pay in full". To encourage consumption of this customer, the credit line usage rate of the month should be raised from below 5% (Category 2) to the level of 5% ~ 10% (Category 3) and total expenditure of the month should increase from below NT$5,000 (Category 2) to NT$5,000 ~ NT$20,000 (Category 3). Therefore, DEA suggests that in the case of this customer, improvements should be made for both risk and the expenditure aspects.

4 Conclusions and Suggestions

The empirical results revealed that the proposed DEA-based customer behavioral scoring model was able to provide specific suggestions on customer categorization. Of the 1000 card holders in the sample, 128 were rated as high-contribution customers, and the rest 872 were judged as low-contribution customers. For these low-contribution customers, specific suggestions in the aspects of payment behavior or consumption were made to enhance their contribution levels. Through the proposed system, banks can provide individual customers with personalized marketing or customized management. Benefits brought about include better control over resources input, comprehensive consideration on risk and revenue, and effective improvement of customer contribution. Due to the constraint on data access, only payment behavior and expenditure amount were used as the input variables in this study. In future studies, practicability of the model can be further enhanced by integrating other factors associated with customer behavior scoring or contribution, such as total amount paid, the purchase of financial instruments, and consumption frequency.

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