Strategy Comparison with Optimization

***SEHYUN JUN*[1]**
***CHOON-KYEONG KIM*[2]**

Abstract

With adaptive (control) technology introduction, lenders have started using adaptive control technology in overall area of credit cycles (collection, acquisition, credit line assignment etc). With the technology being called as "*Champion/Challenger*" in the financial area, lenders, they believe, could have found the optimal operating strategy for all credit cycles. However, with marginal performance difference between *Champion* and *Challenger* or fluctuation in performance, there is still some probability to misread the result between *Champion* and *Challenger*. On top of that, with operating error, clean & controlled comparison between them will not be guaranteed easily in the real business environment. Which means, depending on the operating error, the final decision for selecting one from *Champion* and *Challenger* might be changed.
To solve out this problem, this paper will talk about "*Efficiency*" approach based on DEA analysis. With "*Efficiency*" approach, will outline how lenders to compare the *Champion/Challenger* and how to assign resources to achieve the business' goal.

1. Introduction

In these days, most of financial institutions (mostly banks or credit card companies) are using various strategies in their credit cycles (acquisition, portfolio management, and collection etc). Key feature of these strategies is "Customer Relationship Management" which can interact/communicate with customers purely based on customers' situation

[1] Email: sunjkim@dreamwiz.com

[2] Risk & Reward Consulting, Email: ckkim1553@yahoo.co.kr

(i.e., delinquent, line management, etc). Thus, by using customer's behaviors either credit bureau or internal master file, financial institution makes segmentation groups which are different from each other, but has uniform feature in each own group. For these different groups, financial company is providing different offers to maximize their profit. For example, for credit line increase strategy, the company can offer line increase to "*Low Risk and Max Revenue*"group , but no offer to "*High Risk and Low Revenue*" group. Due to the change of customers' behavior or market environment, the current existing strategy (we call it "*Champion*") will not be a forever golden rule. Which means, the company needs to do efforts to find out the better strategy (we call it "*Challenger*") than the current one forever. Theoretically, by comparing these Champion/Challenger strategies, the company can approach to the better place. However, it is very difficult to implement Champion/Challenger strategy, and even more difficult to measure the actual performance without any bias. In this paper, we would like to review reasons why the comparison between Champion and Challenger might be biased. And also we would like to introduce DEA(Data Envelopment Analysis) to solve the issue that comparing Champion/Challenger has.

2. Collection Strategy

Among all credit cycles areas, collection is the place where most of financial companies are applying their strategies with champion and challenger scheme. Main reason is, first, there are relatively a lot of items that they can test. For example, segmentation test with new bureau information, collection intensity test, number of letter/call test, call sequence test etc. The second reason is, it takes relatively less time to get the impact of successful test (comparing to other area, like credit line increase/decrease. Some countries, financial companies should have customers' consent to do any line increase/decrease). Though collection is good place to execute strategies with champion/challenger, there are a lot of things to keep in mind for monitoring strategies' performance and choosing the final superior one with its results. Uncontrollable noise in collection strategy execution/monitoring might be caused by followings.

1. Many elements can impact on collection performance

: There are so many elements which can influence on the final performance of collection. Though company can set the limit or guideline for numbers of call, letter, collectors, etc for each strategy, however, by nature, we cannot make full control for these elements. Which means, slight difference of these elements for each strategies can make some difference (or make noise) in the collection performance.

2. Small numbers of accounts with big balance can make difference

: Generally, delinquent amount varies by customers. Most of customers' delinquent amounts are within certain amount, but there are usually BIG amount delinquent outliers which has an impact on collection strategy performance. Thus, if a certain collection strategy fortunately can get the delinquent amount from the outlier, then the corresponding strategy would outperform than others. To avoid this kinds of misinterpretation, usually accounts' level also being monitored. However, too much difference between account and amount level performance can make the decision maker confused.

3. Biased interpretation on new strategy performance.

: Generally, new collection strategy has been developed by either risk management analyst or collection dept people or both. And this new strategy performance usually is monitored by them. This fact can cause some bias. Since they develop their new strategy with their big effort, they wish new strategy to outperform to the existing one. Thus, they tend to make decision within a quite short time, if they see some early indicator. In opposite case (new strategy shows worse performance), they tends to cling to some minor excuses, i.e., seasonality, small numbers of bad accounts, etc, until new strategy performance turns out better than the existing one.

4. Test population is not random

: In the actual environment, it is very difficult to find out pure test bed. With continuing challenger/champion test, random numbers assigned to each accounts would be no more random in terms of “Balance”, “Delinquent amounts”, “Utilization” etc. Which means, from starting point of new challenger/champion strategy execution, there are some gaps in terms of performance between Challenger/Champion. Thus, risk manager (or strategy developer) tends to interpret this starting gap with their preference.

5. Big assumption

: Usually, when financial companies decide to choose one strategy as Champion, they do P&L analysis. Major logic behind is, the gain from expected loss save (or expected expense save) or gain between expected loss save and additional expense due to strategic actions(for example, more letters, more calls). However, major big contribution of this analysis is loss save by big assumption (for example, bucket 2+ flow to charge-off). Depending on the selection of observation months for flow-rate-to-charge-off calculation, the final output might be totally different.

6. One measure for successful test

: In the collection area, main focus is to prevent delinquent customer from going into next delinquent status (we call it next bucket with collection terminology). Thus, by nature, all MIS is focusing on how much amount in current month will flow into next bucket every month. In consumer risk area, we call it as “Leading Edge Flow”. Naturally, many financial companies are using this “Leading Edge Flow” as one of success factor (or early indicators) of their strategy performance. However, as final collection performance is the combination of all other resources, we should not depend on one dimensional number for our final conclusion. For example, if we increase numbers of collectors ten times, then we can reduce “Leading Edge Flow” significantly. Thus, all final conclusions should be based on all multi-dimensional numbers from collection operation, rather than just one single number.

As explained above, financial companies might make wrong decision which can have an big impact on their bottom line. Thus, there should be a subjective methodology incorporating all resources and outputs altogether which is able to interpret all collection numbers without any assumption/bias

3. Data Envelopment Analysis

Data envelopment analysis(DEA) is receiving increasing importance as a tool for evaluating the performance of decision making unit(DMU), like manufacturing, service operation(for example, hospital, school, banks). Different from traditional ratio analysis approach, it can handle multiple input- multiple output cases with one single measure "Efficiency".

$$Efficiency = \frac{Weighted\ sum\ of\ outputs}{Weighted\ sum\ of\ inputs} = \frac{\sum_{k=1}^{s} v_k y_k}{\sum_{j=1}^{m} u_j x_j}$$

s : *numbers of outputs*

m : *numbers of inputs*

x_j : *jth input*

y_k : *kth output*

v, u : *weights*

By comparing each decision making units(DMUs) with linear programming, it can assign one optimal and relative efficiency score to each DMUs. Assuming there are *n* DMUs, *m* inputs, and *s* outputs, then the efficiency score for particular DMU *O* can be expressed with below objective function and constraints

$$Maximize \quad \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \qquad (A)$$

$$s.t \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad j = 1, \dots, n$$

$$u_r \geq 0 \ (r = 1, \dots, s) \quad and \quad v_i \geq 0 \ (i = 1, \dots, m)$$

Above non-linear programming formula (*A*) can be transformed into below linear programming form (*B*)

$$\max\ z = \sum_{r=1}^{s} \mu_r y_{ro} \qquad (B)$$

$$s.t$$

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1, \ldots, n$$

$$\sum_{i=1}^{m} v_i x_{io} = 1$$

$$\mu_r, v_i \ge 0$$

With above (B) linear programming, we can get the optimal solution, however, we solve the problem with below Dual problem (*B'*) to (*B*), in order to solve it easily with reduced numbers of constraints.

$$\theta^* = \min\ \theta \qquad (B')$$

$$s.t$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \le \theta x_{io} \quad i = 1, 2, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} \quad r = 1, 2 \ldots, s$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \ge 0 \qquad j = 1, 2, \ldots, n$$

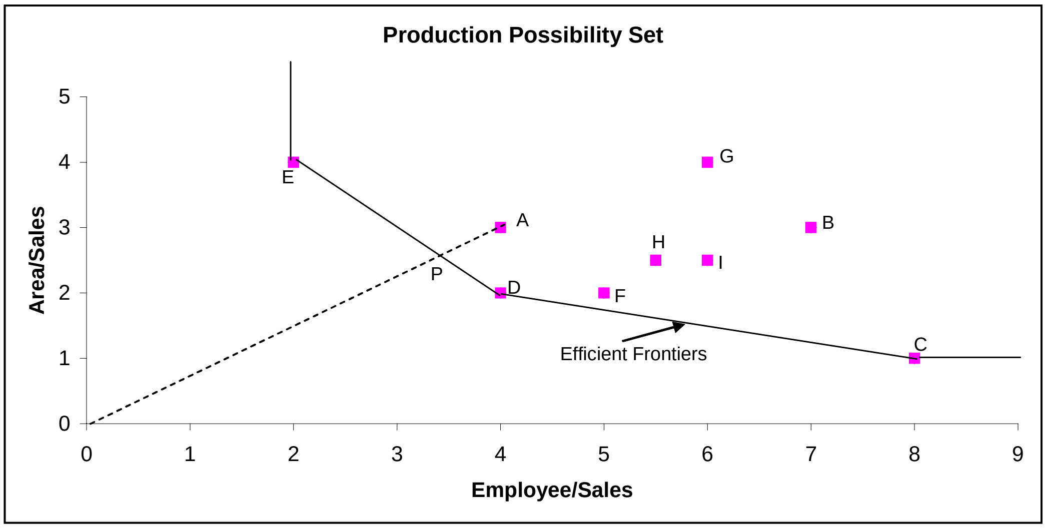
Let's take a look at simple example (Cooper,W.W, et all,2006) which has two input and one output case. Table 3.1 which list the performance of 9 supermarkets each with two inputs and one output. *Input* x_1 is the number of employees(unit:10), *Input* x_2 the floor area(unit: 1000 m^2) and *Output* y the sales (unit: 100,000 dollars). If we plot the Table 3.1, then it would be as Figure 3.1. From the efficiency point of view, it would be natural to judge stores which use less input to get one unit output as more efficient. Thus, we identify the line connecting C, D and E as efficient frontier. And the efficiency of store A which is not on the frontier line can be measured as

$$\frac{OP}{OA} = 0.8571$$

Table 3.1

Store		A	B	C	D	E	F	G	H	I
Employee	x1	4	7	8	4	2	5	6	5.5	6
Floor Area	x2	3	3	1	2	4	2	4	2.5	2.5
Sale	y	1	1	1	1	1	1	1	1	1

Figure 3.1



For each store, with two input and one output, DEA give efficiency value as Table 3.2

Table 3.2

DMU	Input1 *Employee*	Input2 *Floor area*	Output *Sale*	Efficiency
A	4	3	1	0.8571
B	7	3	1	0.6316
C	8	1	1	1.0000
D	4	2	1	1.0000
E	2	4	1	1.0000
F	5	2	1	0.9231
G	6	4	1	0.6000
H	5.5	2.5	1	0.7742
I	6	2.5	1	0.7500

Efficiency value in DEA has maximum value 1 as efficiency and minimum 0 value as inefficiency. As Figure 3.1, store C,D,E have maximum efficiency value as 1 which tell us, they are relatively efficient than other store in terms of input usage and output generation.

4. Problem - Collection Example

Table 4.1 presents the example of collection strategy monitoring. Here we have only two strategies whose results have been monitored for three months (for example, at the month 1, corresponding results are Champ M1, Chal M1). Explanations for each column are as follow.

1. Col#1: Delinquent amount assigned to each strategy at the first day of each month (unit: 1000 dollars)
2. Col#2: Numbers of delinquent accounts assigned to each strategy at the first day of each month (unit: 10)
3. Col#3: Numbers of collectors assigned to each strategy and each months (unit: 10)
4. Col#4: Numbers of calls given to customers by collector at that month (unit 10)
5. Col#5: Rolled-back amount by customers paying out (unit: 1000 dollars) (e,g, 60DPD(days past due) delinquent customer paid out two months amount(this & previous months' amount) and become 30DPD status)
6. Col#6: Current Bucket Staying amount(unit: 1000 dollars): (If customer pay out just one month principal and interest amount, then he will stay current delinquent bucket)
7. Col#7: Numbers of rolled-back accounts (unit: 10)
8. Col#8: Numbers of accounts who are staying at current buckets (unit :10)

Table 4.1

	Col#1	Col#2	Col#3	Col#4	Col#5	Col#6	Col#7	Col#8
Champ M1	340	25	4	400	150	140	10	7
Champ M2	500	15	5	350	180	200	6	6
Champ M3	430	24	7	410	220	170	10	13
Chal M1	400	26	6	450	250	100	8	10
Chal M2	450	20	6	370	200	160	8	10
Chal M3	490	20	5	400	160	200	10	8

As described earlier, two standard measures for evaluating collection strategy are "Leading Edge Flow", which calculate the portion of delinquent amounts migrates into next bucket. Thus, the more flow in "Leading Edge Flow" shows the collection activity was not good enough to prevent from flowing into next buckets. Table 4.2 shows two leading edge flows (accounts, amounts) with Table 4.1

Table 4.2

	Leading Edge Flow (Amount)	Leading Edge Flow (Account)
Champ M1	14.7%	32.0%
Champ M2	24.0%	20.0%
Champ M3	9.3%	4.2%
Chal M1	12.5%	30.8%
Chal M2	20.0%	10.0%
Chal M3	26.5%	10.0%

Table 2 shows Champion strategy looks better in terms of "Amount" basis, but Challenger is better in "Account" basis. Thus, it would make decision maker to be difficult to make any decision for their final collection strategy.

4.1 DEA Approach

In order to compare both Champion and Challenger strategy with DEA approach, we need to define "Input" and "Output". There will be a lot of combination for "Input" and "Output" combination in real collection, but here define them with Table 4.1 as below Table 4.3.

Table 4.3

	Input1	Input2	Output1	Output2	Output3	Output4
	# of Collectors	Numbers of Calls	Rollback Amt/ Starting Amt	(Rollback+Staying) Amt /Starting Amt	Rollback Acct/ Starting Acct	(Rollback+Staying) Acct/Starting Acct
Champ M1	4	400	44.1%	85.3%	40.0%	68.0%
Champ M2	5	350	36.0%	76.0%	40.0%	80.0%
Champ M3	7	410	51.2%	90.7%	41.7%	95.8%
Chal M1	6	450	62.5%	87.5%	30.8%	69.2%
Chal M2	6	370	44.4%	80.0%	40.0%	90.0%
Chal M3	5	400	32.7%	73.5%	50.0%	90.0%

With above Table 4.3, DEA gives all DMU(Champ1,2,3, Chal1,2,3) with efficiency 1. That results caused by main feature of linear programming which assigned the maximum weights first in order to have maximum value of objective function. To solve this issue, introduced "Cross Efficiency Matrix" approach.

A Cross Efficiency Matrix (Sexton et al., 1986) is a table which conveys information how each DMU's relative efficiency is rated by other units. In classic DEA, each DMU is evaludated from only its own point of view, in Cross Efficiency Matrix, each DMU is also evaluated from the other DMUs points of view. Table 4.4 is an example of a Cross Efficiency Matrix. The entry in cell *ij* shows the relative efficiency of unit *j* with the DEA weights optimal for the target DMU unit *i*. For example in Table 4.4 DMU 1 has a relative efficiency of 1 with its own optimal weights set and relative efficiency of 0.8 with the optimal weights for DMU 2. After having a Cross Efficiency Matrix, could compute the average of the efficiencies in each column to get a measure of how the DMU associated with the column is rated by the rest of the DMUs.

Table 4.4

	DMU 1	DMU 2	…	DMU n
DMU 1	1	0.85		0.94
DMU 2	0.75	1		
.				
.				
DMU n				1

Table 4.5 shows the output of CEP(Cross Efficiency Matrix) with collection problem.

And the last two row shows the average of relative efficiencies for each DMU(Champ1,2,3, Chal1,2,3). Though it is not clear, but we can tell that Champion is slightly better than Challenger with CEP approach.

Table 4.5

	Champ M1	*Champ M2*	*Champ M3*	*Chal M1*	*Chal M2*	*Chal M3*
Champ M1	1.0000	0.8502	0.8088	0.7941	0.6989	0.7722
Champ M2	0.6528	1.0000	0.8624	0.6994	0.8979	0.8000
Champ M3	0.5952	0.9113	1.0000	0.7299	0.9446	0.5952
Chal M1	0.5128	0.6901	0.8001	1.0000	0.6325	0.5128
Chal M2	0.6253	0.9404	0.9698	0.7341	1.0000	0.6667
Chal M3	0.5921	0.8625	0.7308	0.5878	0.8020	1.0000
Average	0.66	0.88	0.86	0.76	0.83	0.72
SD	0.17	0.11	0.10	0.14	0.14	0.17

4.2 Extension

Window Analysis

We touched Collection strategy comparison with DEA approach. In our problem, we handled two strategies(Champion/Challenger) with 3 observation points. We can expand this approach, if financial company want to use it as time series ways. Table 4.6 is the example of how we can use DEA approach for strategy comparison with time series. Whenever new data point comes, then the oldest observation will be excluded from efficiency calculation.

Table 4.6: Window Analysis

	1	2	3	4	5	6	7
Champion							
Window1	0.8	0.83	0.84				
Window2		0.82	0.86	0.9			
Window3			0.85	0.87	0.91		
Challenger							
Window1	0.79	0.77	0.79				
Window2		0.8	0.81	0.82			
Window3			0.76	0.82	0.84		

Tracking with Benchmark

Most of financial companies have a benchmark numbers when they develop the collection strategy. For example, for a certain strategy, they set the number of collector as 400, and numbers of calls to the customers like 4000/month. However, when the strategy implemented and evaluated, these benchmark numbers tends to be forgotten, due to comparison between Champion and Challenger only. Thus, sometimes, even though strategy A performance is within the benchmark(but the other B is not), decision maker might throw it away by just looking at his/her preference measure only(like "Leading Edge flow" etc). Table 4.7 shows the Input/Output table together with "Benchmark". With this Input/output table, if analyst makes CEP table only focusing on "Benchmark", then decision maker can get the relative efficiency table comparing with "Benchmark" as Table 4.8.

Table 4.7

	Input1	*Input2*	*Output1*	*Output2*	*Output3*	*Output4*
	# of Collectors	Numbers of Calls	Rollback Amt/ Starting Amt	(Rollback+Staying) Amt /Starting Amt	Rollback Acct/ Starting Acct	(Rollback+Staying) Acct/Starting Acct
Champ M1	4	400	44.1%	85.3%	40.0%	68.0%
Champ M2	5	350	36.0%	76.0%	40.0%	80.0%
Champ M3	7	410	51.2%	90.7%	41.7%	95.8%
Benchmark	**5**	**400**	**60.0%**	**85.0%**	**50.0%**	**95.0%**
Chal M1	6	450	62.5%	87.5%	30.8%	69.2%
Chal M2	6	370	44.4%	80.0%	40.0%	90.0%
Chal M3	5	400	32.7%	73.5%	50.0%	90.0%

Table 4.8

	Champ M1	*Champ M2*	*Champ M3*	*Chal M1*	*Chal M2*	*Chal M3*
Benchmark	0.80	0.99	0.96	1.00	0.98	1.00

Strategy Improvement

Most important output of DEA(linear programming) is the information each DMU is operating on at this current efficiency level. For example, Champions strategy's final efficiency was 0.8, but its number of collector is too much comparing to the efficient operating point(DEA gives how each DMU can reach full efficient operating point).

Thus, by looking at the final output, decision maker can reduce number of collectors to become more efficient. If model was formulated as (B') then the decision maker should set its operating condition like below

$$\begin{cases} \hat{x}_{io} = \theta^* x_{io} - s_i^{-*} \\ \hat{y}_{ro} = y_{ro} + s_r^{+*}, \qquad s_i^{-*}, s_r^{+*} \ \textit{is slack variable} \end{cases}$$

5. Conclusion

In this paper we have introduced DEA and some methodological extensions what could be utilized to improve strategy comparison in collection area. DEA approach can give the analyst/or decision maker the subjective interpretation on strategy performance. On top of that it can give the idea how each strategy can be improved with the output. DEA approach can be utilized in other consumer risk area, like credit line management, customer segmentation, collectors' performance evaluation, and collector incentive assignment based on performance.

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