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USING DATA ENVELOPMENT ANALYSIS FOR EVALUATING EFFICIENCY OF MICROFINANCE INSTITUTIONS IN VIETNAM

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Abstract - Microfinance institutions (MFIs) are very different from conventional financial institutions. They are small in size and mainly provide small collateral free loans. The efficiency of an institution is crucial for long run sustainability. Thus efficiency evaluation of MFIs is indispensable for monitoring and optimal policy implications in the field. Given the lack of previous studies in this issue, the study aims to investigate the technical efficiency and scale efficiency of MFIs in Vietnam via Data Envelopment Analysis (DEA) methods. The empirical results reveal that the average overall technical efficiency scores of MFIs surveyed under input- and output-oriented models are both 91%. Moreover, the study suggests that the sampled MFIs have a potential of increasing efficiency by decreasing the use of inputs while still obtaining the existing output level or increasing the outputs without increasing the use of input level.

Index Terms - Data Envelopment Analysis, Efficiency, Microfinance Institutions, Vietnam.

I. INTRODUCTION

Microfinance institutions (MFIs) are special financial institutions with for-profit and social nature. They have been established to improve the living conditions or socioeconomic wellbeing, as well as set up income-generating activities of the deprived class of society, and poor communities, who are often ignored by the conventional banking system. Basically, MFIs are small in size and often provide small collateral free loans. They are very different from conventional financial institutions.

The efficiency of an institution is crucial for long run sustainability. An efficient MFI is supposed to reach two main goals that are coined as ‘the double bottom line’ [1]-[2], financial intermediation and poverty reduction [3]. The former suggests that MFIs should make enough revenue to at least secure their operating and financial costs [4]-[5] or self-sustainability without the use of subsidies, grants, or other concessional resources [6]. The latter emphasizes the social mission to fight against poverty or the level which microfinance services really help the marginalized community members to get out of poverty trap. In other words, these institutions can generate enough income to repay or cover its opportunity cost of all inputs [7] while still following the social mission. Thus efficiency evaluation of MFIs is indispensable for monitoring and optimal policy implications in the field.

The literature in the component of efficiency analysis is still lacking. In compare to the popular in researching the efficiency of conventional financial institutions that of MFIs are less frequent studied caused by the late emergency of this sector. Therefore, analysis of this issue is of much worth, which is the objective of this paper. The matters here are how should we compare MFIs and to what extent MFIs should focus on to improve their efficiency. Keeping in view the above facts, the study attempts to find out the most efficient MFIs that would be a good example of other MFIs in the country to follow. Measuring the efficiency level of MFIs can be done by using different parametric such as Stochastic Frontier Analysis (SFA), Thick Frontier Analysis (THA), etc. and non-parametric techniques such as Data Envelopment Analysis (DEA) [8]-[1]. This issue has attracted researchers up to the present date and its literature has been developed all the time. References [9] and [10], for example, have used ratio analysis technique, whereas [11] applied stochastic frontier analysis. On the other hand, the DEA has been considered as the popular efficiency assessment technique. It can be used even though the conventional cost and profit function cannot be justified [8]. Another strength of DEA is that it does not require any assumption of distribution and be free from specific functional form. Therefore, this study presents an application of DEA to differentiate efficient from inefficient MFIs.The rest of the study is structured as follows. A short literature review and methodology used to measure MFI efficiency are next illustrated. This section suggested that DEA was an appropriate tool for efficiency assessment. The current study applied the methodology on 27 MFIs in Vietnam with the year of 2014. Next section focuses on the results and discussion. The paper ends with a summary of the findings.

II. LITERATURE REVIEW AND METHODOLOGY

Reference [12] conducted a research applied both qualitative and quantitative techniques, particularly DEA analysis to evaluate the efficiency and effectiveness of MFIs, mainly non-governmental organizations (NGOs) scheme, in Vietnam. As a result, most schemes are fairly efficient with the average technical efficiency score is 76%. The study also applied the SFA and parametric linear programming techniques to measure efficiency. The results are 69%

and 78% respectively. Reference [13] used DEA to measure the efficiency level along with a sustainability assessment of 25 Indian MFIs. Reference [1] followed up DEA to find out which MFIs are efficient and then suggested a methodological approach to explain the efficiency score. Reference [14] in 2010 used DEA with the data from 2007 to 2009 to rank 39 MFIs in India and found only two and six efficient MFIs under constant returns to scale (CRS) and variable returns to scale modeling respectively. In addition, [15] applied DEA to measure the cost efficiency of 39 MFIs across Africa, Asia and Latin America. This might be the first comparative study at the international level. He pointed out that non-governmental MFIs are most efficient ones under production approach, whereas bank-MFIs performed most efficient under intermediation approach. The DEA method was also applied in the study of [16] on agricultural microfinance borrowers in rice farming in Bangladesh. He concluded that the major determinants of inefficiency are land fragmentation, family size, household wealth.

DEA first introduced in 1978 by [17] has been commonly used to evaluate the efficiency in almost every sector of economy. It is a nonparametric method and a simple approach to extract the relative efficiency of production units using linear programming. It compares each decision-making unit (DMU) with only the “best” units. Here the basic DEA model comprised the Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC). At first, the CCR model was developed as an optimization model which presents constant CRS. Then, BCC model as an extension of CCR model was proposed by [18] to allow the existence of variant return to scale (VRS). There are three different forms to define the efficiency in DEA: overall technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE).

TE refers to institution’s success in producing maximum output from a given set of input. If there is k MFIs (DMUs) using n inputs to produce m outputs. For each DMU (k=1,…,k), inputs and outputs are denoted by x_{jk} (j=1,…,n) and y_{ik} (i=1,…,m) respectively. The efficiency of a DMU can be calculated by the following mathematical formulation [19]-[20]-[13]-[6]-[21].

$$\text{Technical Efficiency (TE)} = \frac{\text{sum of weighted output}}{\text{sum of weighted input}} = \text{TE}_k = \theta = \frac{\sum_{i=1}^{m} u_i y_{ik}}{\sum_{j=1}^{n} v_j x_{ik}}$$

Where:

y_{ik}: the quantity of the i^{th} output produced by the k^{th} DMU

x_{ik} : is the quantity of the j^{th} input used by the k^{th} DMU

u_i, v_j: output and input weights

TE_k: technical efficiency ratio

The efficiency score of a DMU cannot exceed one where the input and output weights are positive. The weights are selected in such a way that the DMU maximizes its own efficiency.

$$\left(\frac{\sum_{i=1}^{m} u_i y_{ik}}{\sum_{j=1}^{n} v_j x_{jk}}\right) \leq 1 \qquad u_i, v_j \geq 0$$

An output-oriented linear programming model (OOM) estimates the output of a DMU concerning the best-practice level of a given set of input. To select optimal weights, we follow the below mathematical programming [19]-[20].

Max TE_k

Subject to

$$\sum_{i=1}^{m} u_i y_{ir} - x_{jr} + w \leq 0 \qquad r = 1 \ldots K$$
$$v_j x_{jr} - \sum_{j=1}^{n} u_j x_{jk} \qquad u_i \text{ and } v_j \geq 0$$

Input-oriented linear programming technique (IOM) is applied to obtain the given level of output by minimizing the use of inputs. The mathematical programming model is as follows [19]-[20]:

Min TE_k

Subject to

$$\sum_{i=1}^{m} u_i y_{ir} - y_{iF} + w \geq 0 \qquad r = 1 \ldots K$$
$$x_{jr} - \sum_{j=1}^{n} u_j x_{jk} \geq 0 \qquad u_i \text{ and } v_j \geq 0$$

This model presents CRS if w = 0 and it changed into VRS if w is used unconstrained [22]. The first case refers to TE while the second case shows PTE which is the TE of BCC model assuming that convex combination of the observed DMUs form the production possibility set.

Clearly, if there is a difference in the two TE scores for a given DMU (MFI), it means that the institution has scale inefficiency. If a DMU, for example, has full BBC efficiency but a low CCR score, then it is operating locally efficiency but not globally efficiently due to the scale size of the DMU. Therefore, it is needed to characterize the SE of a DMU by the ratio of the two scores.

Based on the results of CCR and BCC model, SE is defined by [21]:

$$SE = \frac{TE_{CCR}}{TE_{BCC}} \quad \text{or} \quad TE_{CCR} = TE_{BCC} x\, SE$$

Additionally, [23] suggested that if the SE is less than one, the particular DMU might be operating either at decreasing returns to scale (DRS) if a proportional increase of all inputs produces a less-than-proportional increase in outputs or increasing return to scale (IRS) at the converse case. Thus resources may be transferred from DMUs operating at DRS to scale to those operating at IRS to increase average productivity at both sets of DMUs.

In this study, DEA-solver software was used to calculate the efficiency scores.

Selection of Inputs and Outputs

There are two major contexts when observing the operation of MFIs: intermediation and production [24]. The first model means that MFIs can be considered as financial intermediaries. They will make loan and collect deposit to make a profit. They are more or less similar to traditional banks. Inputs in this case may be deposited and acquired loans while output is loans placed. On the other hand, the second model observes MFIs as production units. Specifically, they treat personnel or credit officers and assets as inputs to produce outputs such as disbursement of loans and generating revenue [25]-[13]. The financial institution here uses physical resources to mainly take deposits and lend its funds. The selection of inputs and outputs then depends on how we understand the nature of a financial institution and the availability of data sources.

The sample size of the study includes a total of 27 MFIs in Vietnam depending upon the availability of data, mainly NGO-MFIs, available with latest information on MIX Market Network, a global web-based microfinance information platform, for the year 2014. Because most of MFIs do not provide savings and deposits (except microfinance banks – one kind of MFIs) and keeping into consideration the limitation of same input and output variable for DEA models, the study basically adopted production model when selecting input and output variables.

According to [26], the efficiency/productivity ratios of an MFI are identifying with "how to use the resources, including assets and personnel efficient". MFIs' assets are described as "loans, investments, and other assets expected to produce income", whereas personnel may be defined as either the total number of staffs employed or the number of loan officers.

References [8] and [27] proposed the number of personnel (human resources) as an input. It includes staffs "whose main activity is direct management of a portion of the loan portfolio" [28] or the number of individuals who are actively employed by the MFI. As the data is available, the study uses it as the first input. The second input is total assets (capital structure) that 'include all assets accounts net of all contra-asset accounts, such as the loan-loss allowance and accumulated depreciation' [26].

The gross loan portfolio (output) was selected as measures of outreach and a component of financial indicators [8]-[27]-[20]. This is "the outstanding principal balance of all of an MFI's outstanding loans, including current, delinquent, and restructured loans, but not loans that have been written off" [26]. As the data for the number of loans is not available in the given year, the study uses instead the number of active borrowers as the second output. Reference [26] defined it as 'the number of individuals who currently have an outstanding loan balance with the MFIs or are primarily responsible for repaying any portion of the gross loan portfolio. This number should be based on the number of individual borrowers rather than the number of groups.'

III. RESULTS AND DISCUSSION

Data in Table 1 indicates the correlation between selected inputs and outputs when considering MFIs as production units. Theoretically, the value of a correlation coefficient can vary from minus one to plus one. A minus one score refers to a perfect negative correlation and vice versa. In the first case, when the increase in value of one variable will result in the decrease in value of the other variable. In the second case (positive correlation), the variable moves together. A correlation of zero indicates no relationship between the studied variables. The result found a high correlation among selected input and output.

Table 1: Correlation between Input and Output Sources

	Total assets	Personnel	Gross loan portfolio	Active borrowers
Total assets	1			
Personnel	0.99720145	1		
Gross loan portfolio	0.999310435	0.994471578	1	
Active borrowers	0.990110532	0.980842977	0.99456394	1

Source: Author own calculation

Moreover, Table 2 presents summary statistics of the variables selected as inputs and outputs in the DEA method.

[Table 2 around here]

DEA efficiencies (TE, PTE, and SE) for each MFI were calculated using the CCR and BCC models and reported as follows.

[Table 3 around here]

Table 3 reveals some important features. There are more MFIs show VRS pure technical efficiency than CRS technical efficiency. Specifically, eight MFIs out of 27 MFIs are on the technical efficiency frontier under CCR model assuming a CRS. (TE = 1). Whereas, there are 11 MFIs turning out to be most efficient institutions under BBC model assuming VRS (PTE = 1). Most of them are NGO type institutions providing microfinance services (mainly micro-credit) except VBSP (bank). MFIs that remain efficient under both CRS and VRS are CAFPE BR-VT, CEP, M7 Ninh Phuoc, M7 CDI, MOM, SEDA, VBSP, and WDF Lao Cai. It can be said that these institutions are good at using the inputs to generate lots of loans. Furthermore, the DEA results found out quite high-efficiency scores at 91%, 94%, and 97% for average input-oriented TE, PTE, and SE respectively. This implies that inputs can be decreased by 6% without decreasing in outputs, i.e., gross loan portfolio of MFIs. On the other hand, the respectively mean value of TE, PTE, and SE are 91%, 92%, and 98% using output-oriented measures. This estimation suggests that outputs can be increased by 8% with the existing level of inputs. The pure technical inefficiency is greater than scale inefficiency in both models. In other words, the degree of technical efficiency for most of MFIs is lower than the degree of scale efficiency implying that technical inefficiency of MFIs most of the times is caused by the pure technical inefficiency such as managerial inefficiency rather than the scale inefficiency. This finding also means that a portion of overall inefficiency is in consequence of producing below the production frontier rather than producing on an inefficient scale.

Further the results indicate that the percentage of MFIs experienced IRS and DRS are both 37% under IOM. While under OOM, there are about 33% MFIs showing IRS and nearly 41% MFI showing DRS. Clearly, the resources should be increased in MFIs showing IRS to generate more output. The higher number of institutions showing DRS such as ACE, BTWU and Dariu, moreover, should be considered as they are basically quite large institution in total assets and number of staffs in compared to remaining MFIs.

[Table 4 around here]

Table 4 presents the frequency distribution of DEA results of sampled MFIs under both IOM and OOM. The variation in efficiency level is not much. Regarding overall technical efficiency, majority of MFIs i.e. 62.96% have scores above 90% under IOM and OOM as well. This figure in terms of PTE is 70.37% under both IOM and OOM. Whereas the percentage of MFIs having SE above 90% was 88.89% and 92.59% under input and output-oriented measures respectively. Remarkably, there are a few institutions showing the scores under 70%.

IV. CONCLUSION

This study determined efficient and inefficient selected MFIs with respect to two inputs (total assets and number of staffs) and two outputs (gross loan portfolio and number of active borrowers) via non-parametric approach, DEA, to find out which institutions had the best practices and also provide useful recommendation for decision making in the field.Using DEA helps recognize between technical, pure technical, and scale efficiencies. The mean overall TE is 91% under input- and output-oriented models. Further the results imply that most of the technical inefficiency of the MFIs is resulted from the pure technical inefficiency rather than scale inefficiency. It might be interpreted that the MFIs have been inefficient in using and managing their capital and human resource than operating at the wrong scale of operation. These results propose that, the authority and the manager of MFIs need to consider this sign to improve their efficiency level by investigation on the waste of inputs.The study also suggests that the sampled MFIs have a potential of increasing efficiency by decreasing the use of inputs while still obtaining the existing output level or increasing the outputs without increasing the use of input level. For example, same level of gross loan portfolio can be obtained by reducing the inputs such as number of personnel, a proxy for human resource.

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Table 2: Variable Summary Statistics

	Unit	Mean	Median	Min	Max
Total Assets	USD	277,832,394	1,050,000	27,978	6,379,050,000
Personnel	Number	468	20	5	9,162
Gross loan portfolio	USD	254,943,992	990,663	27,540	6,052,090,000
Active borrowers	Number	285,583	5,060	130	7,100,000

Source: Author own calculation

Table 3: Efficiency Summary of Selected MFIs for the Year 2014

MFI (DMU)	IOM				OOM			
	TE	PTE	SE	RTS	TE	PTE	SE	RTS
3PAD Fund Bac Kan	0.53	0.88	0.61	IRS	0.53	0.56	0.95	IRS
ACE	0.94	0.94	0.99	DRS	0.94	0.94	0.99	DRS
An Phu Development Fund	0.88	1.00	0.88	IRS	0.88	1.00	0.88	IRS
Golden Hand Program	0.83	0.83	0.99	IRS	0.83	0.83	1.00	IRS
BTWU	0.83	0.84	0.98	DRS	0.83	0.85	0.98	DRS
CAFPE BR-VT	**1.00**	**1.00**	**1.00**	**CRS**	**1.00**	**1.00**	**1.00**	**CRS**
Cao Bang Poverty Reduction Fund	0.84	0.88	0.95	IRS	0.84	0.85	0.98	IRS
CEP	**1.00**	**1.00**	**1.00**	**DRS**	**1.00**	**1.00**	**1.00**	**DRS**
Coopbank	0.74	0.75	1.00	DRS	0.74	0.75	1.00	DRS
Credit & Savings Project-WU	0.99	1.00	0.99	DRS	0.99	1.00	0.99	DRS
CWCD	0.90	0.92	0.99	IRS	0.90	0.91	0.99	IRS
Dariu	0.85	0.86	0.99	DRS	0.85	0.86	0.98	DRS
M&D Center	0.97	1.00	0.97	IRS	0.97	1.00	0.97	IRS
M7 DB District	0.97	0.97	0.99	IRS	0.97	0.97	0.99	IRS
M7 DBP City	0.90	0.90	1.00	IRS	0.90	0.90	1.00	DRS
M7 Ninh Phuoc	**1.00**	**1.00**	**1.00**	**CRS**	**1.00**	**1.00**	**1.00**	**CRS**
M7 STU	0.96	0.96	1.00	IRS	0.96	0.96	1.00	IRS
M7CDI	**1.00**	**1.00**	**1.00**	**CRS**	**1.00**	**1.00**	**1.00**	CRS
MOM	**1.00**	**1.00**	**1.00**	**CRS**	**1.00**	**1.00**	**1.00**	CRS
PPC	0.99	0.99	1.00	DRS	0.99	0.99	1.00	DRS
SEDA	**1.00**	**1.00**	**1.00**	**CRS**	**1.00**	**1.00**	**1.00**	**CRS**
Thanh Hoa MFI	0.95	0.96	0.99	DRS	0.95	0.96	0.99	DRS
TYM	0.81	0.82	0.99	DRS	0.81	0.82	0.99	DRS
VBSP	**1.00**	**1.00**	**1.00**	**CRS**	**1.00**	**1.00**	**1.00**	**CRS**
WDF, Lao Cai	**1.00**	**1.00**	**1.00**	**IRS**	**1.00**	**1.00**	**1.00**	**IRS**
Women Economic Development Fund-HCM	0.79	0.92	0.85	CRS	0.79	0.90	0.87	CRS
WV Vietnam	0.89	0.89	0.99	DRS	0.89	0.90	0.99	DRS
MEAN	0.91	0.94	0.97		0.91	0.92	0.98	

Source: Author own calculation

Table 4: Frequency Distribution of Efficiency Results

Efficiency	IOM						OOM					
	TE	%	PTE	%	SE	%	TE	%	PTE	%	SE	%
<0.5	0	0	0	0	0	0	0	0	0	0	0	0
0.51-0.6	1	3.70	0	0	0	0	1	3.70	1	3.70	0	0
0.61-0.7	0	0	0	0	1	3.70	0	0	0	0	0	0
0.71-0.8	2	7.41	1	3.70	0	0	2	7.41	1	3.70	0	0
0.81-0.9	7	25.93	7	25.93	2	7.41	7	25.93	6	22.22	2	7.41
0.91-1	17	62.96	19	70.37	24	88.89	17	62.96	19	70.37	25	92.59
Total	27	100	27	100	27	100	27	100	27	100	27	100
Min	0.53		0.75		0.61		0.53		0.56		0.87	
Max	1.00		1.00		1.00		1.00		1.00		1.00	
Mean	0.91		0.94		0.97		0.91		0.92		0.98	
SD (%)	10.84		7.21		7.99		10.84		10.29		3.18	

Source: Author own calculation

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