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Essays in efficiency and productivity analysis of microfinance institutions

Doctoral Dissertation

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Introduction and summary

The financial capital is an essential requisite to unlocking the entrepreneurial potentials of the poor inside the poverty trap. However, access to finance was not always possible as the traditional banking system often looked at poor entrepreneurs as a financially unviable proposition, involving a risk-return pattern that was attractive, given the limited size of their expected transactions and the related expected return. This means that the poor had no alternative but to rely on informal financial markets which are normally based on small size, short-term transactions and, particularly, on moneylenders who, quite often, exploited them with very stiff and high interest rates over the years. In this backdrop, the concept of microfinance that adheres to the principles of both financial as well as social capital emerged to help ease this constraint, at least to some extent. However, at the early stages, programs focused on credit distribution based on administrative criteria by state-owned agricultural development banks, with little concern for program efficiency and effectiveness. The poor performance of these programs eventuate in political interventions, forcing most programs to become insolvent and unviable, causing further donor support to be denied (Von Pischke, 1991; Yaron, 1992a & 1994). In an attempt to attenuate the negative externalities associated with the old-paradigm, many states started to adopt prudent fiscal and monetary policies, supportive regulatory frameworks and financial innovations to expand the financial frontier outward in order to build a cost efficient financial intermediation system (Adams et al., 1984; Yaron et al., 1997). The effectiveness of the new-paradigm of microfinance programs is evidenced by several successful episodes in recent past, including: The Bank for Agriculture and Agricultural Cooperatives in Thailand, Bank Rakyat Indonesia's Unit Desa System and BancoSol in Bolivia (Yaron, 1992a; Glosser, 1994). These achievements challenge the traditional believe that emphasizes the prerequisite of subsidies to work well with the threefold objective of microfinance programs – i.e. social outreach, impact and financial sustainability. These three targets are often mutually excluding and a contemporaneous achievement requires innovation, as well depicted in the microfinance triangle (Zeller & Meyer, 2002). However, not all the experiences are equally successful and there is increasing concern that many microfinance programs across the world are heavily dependent on subsidies (Robinson, 2001; Quayes, 2012). The natural question which is then raised include whether all subsidy-dependent MFIs are underperformers. This question is very important especially for donors and states as they need a criterion to determine the continuation of funding support to MFIs. Balkenhol (2007) argues that such a criterion must encompass both financial and social performance of MFIs. He suggests that irrespective of overall orientation of MFIs, efficiency helps determine, with much better accuracy, between support-worth and underperforming MFIs. Efficiency then becomes more fact based for funding decisions for the states and donors. On the other hand, benchmarking on the basis of sustainability and outreach dimensions of efficiency can help the MFIs to restructure their policy choices to compete in the crowded marketplace.

In light of this scenario, the research conducted in this thesis contributes in the assessment of the ability of MFIs to transform their resources (i.e. technology, employees, infrastructure) to achieve the dual objectives of sustainability and outreach. The dissertation consists of three essays, each exploring the efficiency and productivity dynamics of MFIs in presence of environment impacts.

The first essay examines technical efficiency and its determinants of 36 microfinance institutions in Sri Lanka using a two-stage double bootstrap approach. Efficiency levels are explored in terms of MFIs' dual objectives of financial sustainability and outreach. In the first stage, a bootstrap Data Envelopment Analysis (DEA) procedure is used to correct the bias and construct confidential intervals for the efficiency estimates. Then in the second stage, bias-corrected efficiency estimates are regressed on a set of environmental variables using a bootstrap regression approach. The results of the first stage analysis confirm the existence of financial and social inefficiency for the majority of MFIs in Sri Lanka. The second stage analysis suggests that such inefficiency is determined by a number of MFI characteristics such as its age, its organizational type (i.e. run as an Non-governmental Organization or not), its capitalization level, and its profitability.

The second essay uses a non-parametric Malmquist method to investigate the changes in productivity of 20 Kenyan microfinance institutions over the period 2009-2012. Productivity change is decomposed into indices of technological change, pure efficiency change and scale efficiency change. A bootstrap procedure is employed to construct confidence intervals for the Malmquist indices. This procedure makes it possible to investigate whether such changes are significant in a statistical sense. Additionally, a second-stage bootstrap procedure is employed to ascertain the sources of productivity change measures. Results show that productivity growths are primarily attributable to technical improvements at an average of 7%. Moreover, second stage results suggest that matured MFIs tend to have a lower productivity compared to the younger counterparts.

In the third essay, focus is shifted to investigate the relationship between efficiency and corporate governance in MFIs. Using a two-stage bootstrap procedure for a sample of 36 Sri Lankan MFIs, it explores the effect of several governance models (i.e. board size, proportion of women on the board, duality and presence/ absence of a female chief executive officer) on sustainability and outreach dimensions of efficiency estimates. Results suggest that financial efficiency improves with a small board and higher proportion of women on the board. Results also show that MFIs in which the same individual holds CEO and chairman of the board and MFIs in which a woman holds the position of CEO are less efficient in terms of reaching the lower strata of the rural poor.

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Efficiency of microfinance institutions in Sri Lanka: A two-stage double bootstrap DEA approach

Abstract

This study examines technical efficiency and its determinants of 36 microfinance institutions (MFIs) in Sri Lanka using a two stage double bootstrap approach. In the first stage of the analysis, bias-corrected Data Envelopment Analysis (DEA) efficiency estimates for the individual MFIs are obtained by means of the smoothed homogeneous bootstrapped procedure (Simar & Wilson, 2000) and then they are regressed on a set of explanatory variables employing the double bootstrap truncated regression approach (Simar & Wilson, 2007). Two different DEA models are designed to obtain DEA scores along financial and social perspectives. According to the results from the first stage, many MFIs in Sri Lanka do not escape criticism of financial and social inefficiency. Second stage regression reveals that age and capital-to-assets are significant determinants on financial efficiency whereas age, type of the institution and return-on-assets are the crucial determinants of social efficiency.

1. Introduction

Ratio indicators, parametric and non-parametric methods are the commonly used methods to measure the efficiency. Among these methods, financial ratios can be recognized as a traditional approach to monitor the performance of MFIs. Measuring efficiency of MFIs based on the notion of these ratios is, however, quite distorted unless they have been properly adjusted. These adjustments may include: subsidy adjustments that account for reduced costs (subsidy on personnel, for example) or donation contribution to income of the institution (Yaron & Manos, 2007), inflation adjustments to recognize the loss in the real value of equity, adjustments for non-performing loans in order to compare MFIs on a consistent basis and adjustments to foreign exchange gains/ losses (CGAP, 2003). Despite the undeniable better accuracy of adjusted data, estimates on the adjustments are not always easy to make and data are seldom available. Moreover, ratios in isolation provide little help when considering the effects of economies of scale; the identification of benchmarking policies and the estimation of overall performance measures of firms (Athanassopoulos & Ballantine, 1995). On contrary, frontier methods become more sophisticated and powerful way of benchmarking the firms (Berger & Humphrey, 1997). Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis are the commonly used frontier techniques to measure the efficiency of microfinance programs. Readers interested in detail discussion about the strengths and weaknesses of both methods are encouraged to consult Berger & Mester (1997); Bauer et al. (1998).

In the present paper, we use DEA to examine the technical efficiency and its determinants of 36 MFIs in Sri Lanka. Among emerging financial markets in South Asian countries, the study of MFIs in Sri Lanka is particularly interesting as microfinance plays a significant role in growth of country's economy. Especially after the tsunami devastation in 2004, there was an influx of donor funds into the microfinance sector in Sri Lanka and, consequently, a number of NGO-MFIs emerged (Microfinance Industry Report, 2010). In addition, the end of three- decade long conflict in 2009 creates a better environment for microfinance investors. Nevertheless, prevailing legal constraint due to delay in enacting the proposed microfinance bill inhibits the growth and expansion of microfinance industry. While regulation is sometimes considered more a burden than a booster of microfinance (Adams & Fitchett, 1992), it is often considered a preliminary step. This legal vacuum applies especially on NGO-MFIs as they are not authorized to accept public deposits and obtain off-shore debt and equity funding (Microfinance industry report, 2010). Thus, the findings of this study may provide some insights to the policy makers to develop appropriate policies in order to streamline the microfinance operations in Sri Lanka. This study could also help MFIs to improve their viability, identify the market competition and build appropriate business strategies to compete with better performers in the market. Donors and states, on the other hand, could use the benchmarking results to make funding decisions. Additionally, focusing on a single country in the current study helps to obtain a geographically homogeneous sample.

In contrast to the previous empirical studies using deterministic DEA approaches that carry with them several well known drawbacks, notably, our study contributes to the existing literature by proposing the use of a two stage double bootstrap method. In the first stage of the analysis, the DEA efficiency estimator is corrected for bias using the homogeneous bootstrap procedure (Simar & Wilson, 2000) and then in the second stage bias corrected-efficiency scores are regressed on a set of explanatory variables by employing the truncated regression with bootstrap (Simar & Wilson, 2007). The DEA bootstrap method employed in the current study allows us to obtain more meaningful conclusions as this approach accounts for the bias and serial correlations of efficiency estimates and, consequently, provides valid inference (see Simar & Wilson, 2007). This method is a remedy to the limitations of conventional DEA and SFA techniques and also issues raised by small sample size (Barros et al. 2010). To the best of our knowledge, this is the first empirical study to investigate the efficiency of MFIs in Sri Lanka.

Moreover, despite the importance of measuring both financial and social performance of MFIs, the microfinance literature reveals that there are few studies that have assessed both dimensions of efficiency (Gutiérrez-Nieto et al., 2009; Piot-Lepetit & Nzongang, 2013; Lebovics et al., 2014) while other studies have tended to focus only on financial aspects. Among them, only Lebovics et al. (2014) attempt to shed light on the drivers of efficiency from both financial and social perspectives in a second stage multiple regression analysis. In the present paper we design two DEA models to obtain both financial and social efficiency estimates. Then, they are separately regressed on several potential environmental variables. The second stage results explain the variations in the both dimensions of efficiency estimates.

Our results in the first stage of the analysis show that all NGO-MFIs fail to simultaneously perform well on both financial and social dimensions of efficiency. On the other hand, the empirical results of the second stage regression reveal that older MFIs are financially efficient but socially inefficient. The evidence also suggests that NGOs are socially more efficient. Moreover, our results show that more finically efficient MFIs use leverage as the main source of their capital base. Finally, we find a negative relationship between ROA and social efficiency.

The reminder of the paper is structured as follows: the study begins with an outline of microfinance industry in Sri Lanka. Then, section three provides a brief literature review on the previous application of parametric and non-parametric techniques to measure the efficiency of MFIs. Section four is dedicated to the methodology. Section five discusses the empirical results. Section six concludes.

2. An overview of the microfinance sector in Sri Lanka

2.1 Institutional types

The microfinance sector of Sri Lanka comprises several entities of which no single blueprint model can be found. Apart from government affiliated institutions that claim a large share of the microfinance market in the country, a number of organizations serve the poor in different market niches. Generally, there are four MFIs categories based on regulatory and supervisory mechanism. These are: Licensed Specialized Banks (LSBs), Non Bank Finance Institutions (NBFIs), Cooperatives and NGO-MFIs. LSBs, NBFIs are regulated and registered under the purview of the Central Bank of Sri Lanka (CBSL) while Cooperatives are regulated and supervised by the Department of Cooperative Development (DCD). However, the standard and methods of supervision of these institutions are not uniform due to absence of single regulatory and supervisory mechanism (Microfinance Industry Report, 2010). On the other hand, companies and NGOs, collectively called NGO-MFIs are neither supervised nor regulated by any external authority, yet they are encouraged to be self-regulated. Even though self-regulation that essentially includes the standard accounting and reporting practices is a very important element of enhancing the overall performance, many NGO-MFIs are ill-equipped to deal with self-regulatory mechanisms. On the whole, the prevailing legal vacuum results in many unregulated MFIs in Sri Lanka to suffer from high transaction costs, weak governance mechanism, low repayment rates and recurring losses (Asian Development Bank Completion Report, 2012).

Table 1 illustrates a brief summary of MFIs in Sri Lanka for year 2010. All the monetary values given in the present paper are measured in Sri Lanka Rupees (LKR) unless otherwise stated. As can be seen from the table, the largest number of borrowers and the highest number of offices of LSBs among all groups shed light on their wide outreach spectrum. This view is further supported by the value of loan portfolio. On the other hand, when considering the average loan balance, a proxy for the depth of outreach (Schreiner, 2002), companies and NGOs report comparatively lower average loan balance reflecting their commitment to reach the poor in rural areas. According to LMFPA (2012), most NGOs have an array of social goals whereas companies have a more balanced approach and focus on a few selected development goals. In general, no single type of institution presents an optimal solution to reaching all market segments with all type of financial services in Sri Lanka microfinance market.

Table 1

Summary of the microfinance industry in Sri Lanka.

Institution Type	Regulatory status	Number of borrowers	Loan Portfolio (LKR' million)	Average loan balance (LKR)	Number of offices
LSBs	Regulated & supervised by CBSL	959,498	50,801	50,675	329
NBFIs	Regulated & supervised by CBSL	NA	NA	23,649	NA
Cooperatives	Regulated & supervised by DCD	34,412	1,103	63,817	143
Companies	Self-regulated	379,981	7,406	20,816	302
NGOs	Self-regulated	44,991	785	22,189	164

LSBs: Licensed specialized banks; NBFIs: Non bank finance institutions; CBSL: Central bank of Sri Lanka; DCD: Department of cooperative development.
Source: LMFPA (2012)

2.2 Sources of funding

Deposit, debt and equity are the main source of funding of MFIs in Sri Lanka, with a decreasing weight of donations after the tsunami in 2004. Regulated MFIs such as LSBs, NBFIs and Cooperatives are able to build a large part of their capital base through savings mobilization. Thus, they are able to expand their service range at the frontier while minimizing the dependence on donor funding, the information problems and issue of liquidity management (see Adams et al., 1984; Yaron, 1992b; Hulme & Mosley, 1996). However, because of prevailing legal restrictions on taking public deposits, borrowing from wholesale lending agencies such as Sri Lanka Savings Bank (SLSB), Stromme Microfinance (SMAGL) and Consorzio Etimos Lanka (ETIMOS) is the main source of funding of many NGO-MFIs (LMPA, 2011). Alternatively, several MFIs are debt financed by their promoter institutions to establish revolving loan fund while very few are able to finance their loan portfolio through commercial loans (LMFPA, 2012). Nevertheless, commercial loans are somewhat of an issue as local commercial banks are still reluctant to lend to the microfinance sector due to the perception of high risk (Microfinance industry report, 2010). Equity investment in MFIs is the other potential alternative, but not very common in Sri Lanka due to lack of regulation for raising off-shore equity funds (Legal study on the microfinance sector in Sri Lanka, 2010).

3. Brief review of the literature on efficiency measurement of microfinance institutions

There are several studies that employ either SFA or DEA to examine the efficiency of MFIs. We, however deem that discussing the theory and applications of SFA in MFIs is out of the scope of the present paper, yet following a brief review of SFA applications in earlier studies may be helpful.

Paxton (2007) uses the SFA to examine the 190 semiformal financial institutions in Mexico and discovers that technology, average loan size, rural outreach and age of institution are all positively associated with technical efficiency. Hermes et al. (2008) examine the possible trade-off between depth of outreach and efficiency of MFIs by applying SFA. The results show that outreach is negatively related to the efficiency. By employing SFA, Servin et al., (2012) analyze the technical efficiency of 315 MFIs operating in 18 Latin American countries. Their results suggest that differences in efficiency are associated with the differences in ownership types (i.e., NGOs, cooperatives and credit unions, NBFI, and banks).

On the other hand, regardless of several inherent limitations with the DEA, its popularity remains largely undiminished in microfinance literature. A brief review of the empirical application of DEA in MFIs is summarized as follows.

Nghiem et al. (2005) examine the technical efficiency of 46 microfinance schemes in Vietnam. Employing two inputs (labor costs and non-labor costs) and three outputs (number of savers, number of borrowers and number of groups), they conclude that average technical efficiency of all microfinance schemes is 80 percent and age and location of the schemes influence on the efficiency. Gutiérrez-Nieto et al. (2007) consider the efficiency of 30 MFIs in Latin America. Accommodating two inputs (number of credit officers and operating expenses) and three outputs (interest and fee income, gross loan portfolio and number of loan outstanding), their finding illustrates that efficiency is influenced by the location of MFIs (country effect) as well as institutional type (NGO and non-NGO status). Gutiérrez-Nieto et al. (2009) investigate the relationship between social and financial efficiencies, as well as relationship between efficiency and other indicators (profitability, type of institution and geographical location), for a sample of 89 MFIs in different continents by employing three inputs (assets, costs, employees), two financial outputs (loans and revenues) and two social outputs (number of women borrowers and poverty reach index). The results of their study reveal that low positive relationship between outreach and financial efficiency. Their results further reveal that no socially efficient but financially inefficient MFIs exist. Bassem (2008) investigates the efficiency of 35 MFIs from in Mediterranean zone during the period of 2004-2005 and concludes that the size of the institutions negatively affect their efficiency. Haq et al. (2010) estimate cost efficiency of 39 MFIs across Asia, Africa and Latin America. They find that NGO-MFIs are more efficient under the production approach.

Furthermore, by employing DEA, Segun & Anjugam (2013) examine the efficiency of 75 MFIs in 25 Sub Saharan African countries. The empirical findings reveal that MFIs are inefficient in meeting the goals of either providing microfinance related services to their clients or intermediating funds between borrowers and depositors. Lebovics et al. (2014) use DEA for a sample of 28 MFI in Vietnam. Input variables are total liabilities, operating costs and number of staff while financial output is measured by the gross loan portfolio and the financial revenue while social output by a poverty outreach measure based on Gutierrez-Nieto et al. (2009) and the number of depositors as the offer of savings products is still meager in Vietnam and considered socially very beneficial. Their outcomes show no relation between social and financial efficiency. In addition, using DEA, Piot-Lepetit & Nzongang (2014) investigate the possible trade-off between outreach and sustainability within 52 Village banks in Cameroon and find that majority of the institutions in the sample do not show trade-off. More recently, Bassem (2014) employees DEA based Malmquist productivity index to examine the total factor productivity of 33 MFIs operate in Middle East and North African region over the period from 2006 to 2011. He found that overall productivity decline in MENA region during this period.

Based on our review of the literature using the non-parametric approach, we note several remarkable limitations in extant literature. First, all studies reviewed are based on conventional DEA estimators which are biased by construction and are sensitive to the sampling variations of the obtained frontier (Simar & Wilson, 1998 & 2000). Thus, the results based on conventional DEA approaches are inconsistent. Second, several studies (Nghiem et al., 2005; Segun & Anjugam, 2013; Lebovics et al., 2014) use a Tobit regression to investigate the determinants of the efficiency estimates. However, as pointed out by Simar & Wilson (2007), DEA estimates used in a second stage are biased and serially correlated and thus standard methods for inference in the second stage regression are invalid. In addition, we find that some studies (Gutiérrez-Nieto et al., 2007 & 2009; Bassem, 2008; Haq et al., 2010; Segun & Anjugam, 2013; Piot-Lepetit & Nzongang, 2014) focus on cross country analysis. However, it is worthwhile to note that cross country measures may not fully acknowledge the significance of country characteristics such as state macroeconomic environments (eg: complexities associated with inflation and interest rates, availability of interest rate ceilings), policy induced shocks (Berger, and Humphrey, 1997) and differences in regulatory framework and level of competition in domestic markets (Flückiger & Vassiliev, 2007). Thus, it makes more sense to compare the efficiency of MFIs within the same country than cross country analysis (Balkenhol, 2007). Moreover, we find some studies (eg: Gutiérrez-Nieto et al., 2007 & 2009) using samples that consist of different regulatory status (i.e., banks, cooperatives, credit unions, NBFIs, NGOs etc). Some of these institutions provide range of financial services including savings mobilization whereas the others restrict to providing only credit facilities (credit-only MFIs). Thus, application of such heterogeneous samples in DEA benchmarking may violate the thumb rule of homogeneity assumption of DEA benchmarking (see Golany & Roll, 1989, for discussion on sample homogeneity requirements in DEA).

In contrast to the previous literature, in the current study we employee a two stage double bootstrap approach to investigate both dimensions of efficiency and their determinants of 36 MFIs in Sri Lanka. This innovative method takes into account the bias and serial correlations of efficiency estimates and thereby provides statistically significant results.

4. Methodology

4.1 First-stage DEA efficiency estimate

In the first stage of the analysis, we execute the input oriented CCR model (Charnes et al., 1978) where we assume that managers of NGO-MFIs have less control over the output quantities compared to the available input resources. Consider that there are n MFIs and each produces single output m by using k different inputs. For the i^{th}MFI input and output data are given by the column vectors x_i and y_i respectively. The date for all n MFIs are given by input matrix X (K x n) and output matrix Y (M x n). Then, the input-oriented DEA efficiency estimator for the i^{th} MFI is obtained by solving the following linear programming problem:

$$min_{\hat{\theta}_i^{CRS}\lambda_i}\hat{\theta}_i^{CRS}$$

$$s.t.\quad Y\lambda - y_i \geq 0 \qquad (1)$$

$$x_i\hat{\theta}_i^{CRS} - X\lambda \geq 0$$

$$\lambda \geq 0$$

Where $\hat{\theta}_i^{CRS}$is the technical efficiency of the i^{th}MFI under the constant returns to scale (CRS) assumption and λ is an n x 1 vector of constant. The resulting score ranges between 0 and 1. The benchmark MFIs in the sample claim for the highest efficiency score of 1 and they lie on the constructed frontier. On the other hand, MFIs that are assigned the score less that 1 are relatively inefficient and their input and output values locate some distance away from the corresponding reference point on the production frontier.

4.1.1 Smoothed homogeneous bootstrapped DEA based procedure

Even though the conventional DEA technique has widely been applied, it still suffers from several inherent constraints. One of the main limitations is that it has no statistical properties and consequently leads to generate biased DEA estimates. This major constraint limits the DEA’s usefulness to decision makers (Ferrier, & Hirschberg, 1997) as point estimates of inefficiency offer no discussion of uncertainty surrounding the estimates due to sampling variations (Simar & Wilson, 2000). Hence, we employed the bootstrap concept (Efron,1979) that relies on a simple idea of repeatedly simulating the data generating process (DGP) and applying the original estimator to each simulated sample so that resampled estimates mimic the sampling distribution of the original estimator (Simar &

Wilson, 1998). The empirical distribution of resampled estimates can be used to construct the bootstrap confidence intervals (Lothgren, 1998). In particularly, we take the route initiated by Simar & Wilson (2000) to adopt the homogeneous bootstrap algorithm in first stage of the analysis.

4.2 Second-stage truncated regression

Though widely employed, use of censored models in the second stage of analysis has been criticized by Simar & Wilson (2007). In their studies with Monte Carlo experiments, Simar & Wilson, (2007) demonstrate the limitations of censored models, and propose an alternative double bootstrapped procedure that permits the valid inference and take account of the bias due to serial correlation of the efficiency estimates. Thus, following, Simar & Wilson (2007), we employee the double bootstrap method (Algorithm 2) where the bias-corrected efficiency scores ($\hat{\theta}_i^*$) yielded in the first stage of the analysis are regressed on a set of explanatory variables (z_i) using the following regression specification:

$$\hat{\theta}_i^* = a + z_i\beta + \varepsilon_i, \quad i = 1, \ldots, n \qquad (2)$$

Where a is a constant term, β is a vector of parameters and $\boldsymbol{\varepsilon}_\mathbf{i}$ is the statistical noise. The double bootstrap procedure (Algorithm 2) proposed by Simar & Wilson (2007) involves seven steps, that are presented below.

1. Use the original data to compute the efficiency scores $\hat{\theta}_i^{CRS}$ by solving the linear programming model (1) for each MFI i (i = 1,…,n).
2. Use the method of maximum likelihood to compute the parameter estimates $\hat{\beta}$ and the standard error $\widehat{\sigma_\varepsilon}$ from the truncated regression of $\hat{\theta}_i$ on z_i in (2).
3. Repeat the following four steps (a – d) B1 times for each MFI i (i = 1,…,n) to obtain a set of bootstrap estimates $B_i = \{\theta_{i,b}^*, b = 1, \ldots, B1\}$;
   a. For each i = 1,…,n, ε_i is drawn from N(o, $\widehat{\sigma_\varepsilon}$).
   b. For each i = 1,…,n, compute $\theta_i^* = z_i\hat{\beta} + \varepsilon_i$, i = 1,..,n.
   c. Construct a pseudo data set (x^*_i,y^*_i) where $x^*_i = x_i$, and $y^*_i = y_i\widehat{\theta_i}/\theta_i^*$, for all i = 1,…,n.

d. Compute $\widehat{\theta_i^*} = \theta(x_i, y_i)$ by replacing (x_i,y_i) by (x^*_i,y^*_i), for all i = 1,…,n.

4. For each MFI i = 1,…,n, compute the bias-corrected estimator.

5. Use the maximum likelihood method to estimate the truncated regression of $\hat{\theta}_i^*$on z_i to yield estimates $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}_\varepsilon$.

6. Repeat the following three steps (e - g) B2 times to yield a set of bootstrap estimates $\left\{\left(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}_\varepsilon{}^*, b = 1, \dots, B2\right)\right\}$

   e. For each MFI i = 1,…,n, ε_i is drawn from the N(o, $\hat{\hat{\sigma}}_\varepsilon$).

   f. Compute $\hat{\theta}_i^* = z_i \hat{\hat{\beta}} + \varepsilon_i$ for each MFI i = i,…,n.

   g. Use the maxim likelihood method to estimate the truncated regression of $\hat{\theta}_i^*$on z_i to yield estimates $\hat{\hat{\beta}}^*$ and $\hat{\hat{\sigma}}_\varepsilon{}^*$.

7. Construct the confidence intervals for the efficiency scores.

4.3 Data

Data are collected for 36 MFIs in Sri Lanka for the year 2010. The source of the data used in this study is the report on *"Microfinance Review"* published by Lanka Microfinance Practitioners' Association (LMFPA, 2011). All NGO-MFIs, on which data are available, are included in the empirical study. However, all regulated MFIs and commercial banks in our observations that act as outliers are candidates for elimination from the analysis. The real names of MFIs in our observations are not disclosed in order to preserve their anonymity. The names of MFIs are represented by numbers (1, 2, 3, …, 36). For the missing value of number of female borrowers of the MFI (represented by number "11"), we use the mean value of its nearest neighbors.

4.4 Selection of input and output variables

Selection of input and output variables has to be done carefully, as choices of highly correlated variables may result in multicollinearity issue. Moreover, the selected input and output measures need to be consistent with the approach to be employed. There are two well-recognized approaches: production approach and intermediation approach (Sealey & Lindley, 1977). Under the production approach, the financial institutions are defined as production units that produce services for their customers by using resources such as labor, technology, material and the associated costs. On the other hand, the intermediation approach views the financial institutions as intermediaries that employ labor, deposits and physical capital to produce loans and securities and other investments. The main demerit of these approaches is their failure to address the role of deposits. Production approach recognizes the deposits as output while the intermediation approach takes the deposits as input to production of loans. Despite the actual critical function that deposits may have in affecting the intermediaries' performance, their role becomes an irrelevant factor in the present paper as all MFIs in our analysis are not allowed to accept deposits from public. The next important factor with DEA is referred to the number of input and output variables to be employed. The number of variables to be selected depends on the sample size. Some scholars (Stern et al., 1994; Cooper et al., 2001) argues that sample size needs to be at least three times larger than the sum of number of input and output variables in order to make sure to enhance the discriminatory power in the model. Our choice for selecting input and output variables among the data that are available in consistent basis is also influenced by the previous literature to evaluate the efficiency of MFIs by applying DEA. Descriptive statistics of the input and output variables appear in Table 2. The definitions of input and output variables used in the present paper are based on the Mix market taxonomy[1]. Three discretionary inputs such as

[1] http://www.mixmarket.org/about/faqs/glossary

total assets, number of credit officers and cost per borrower are included and they are common to both financial and efficiency models. Total assets that show little variability in the short term (Hunter & Timme, 1995) has widely been used in early empirical studies as an input variable to measure the efficiency of MFIs (Gutiérrez-Nieto et al., 2009; Piot-Lepetit & Nzongang, 2013) as well as of commercial financial institutions (Seiford & Zhu, 1999; Barth et al., 2013). Because of a large segment of the clients of NGO-MFIs are from the rural, many institutions in our sample use the lending technologies such as solidarity group and individual lending through community based organizations. As a result, a great part of the business role of MFIs including identifying potential clients, screening, negotiating, determining the risk of each loan, disbursement and close monitoring of repayment and most importantly keeping mutual respect is entrusted on the shoulders of credit officers. Thus, based on similar studies (Qayyum, & Ahamad, 2006; Gutiérrez-Nieto et al., 2007; Segun & Anjugam, 2013), number of credit officers is included as a measure of input. The third input variable is the cost per borrower that indicates the operation expenses of MFIs. It has been employed in several early studies (Qayyum & Ahamad, 2006; Haq et al., 2010; Segun & Anjugam, 2013) as an input variable. On the other hand, we specify output variables based on the financial and social objectives of MFIs. The financial efficiency model is built by assigning the financial revenue as the output variable whereas the total number of female serves as the measure of output in social efficiency model. The number of female borrowers is an indirect proxy for depth of outreach as it takes into account women discrimination by social norms (Yaron et al., 1998) and, as a consequence, allows focusing on the poorest customers. Kar (2012) argues that MFIs with a large number of female borrowers indicate *"a better quality outreach to the poor"*. Hence, selection of number of female clients over the other possible depth of outreach proxies is more appropriate in the context of microfinance industry in Sri Lanka where many rural women suffer social deprivation that lead to erode their entrepreneurial prospects (Shaw, 2004).

Table 2

Summary of descriptive statistics of input and output variables

Variable	Mean	Std. dev.
Total assets (LKR'000)	305,233	900,963
Number of credit officers (Number)	48	104
Cost per borrower (LKR'000)	4	5
Financial revenue (LKR'000)	59,298	141,651
Number of female borrowers (Number)	9,133	19,256

Std. dev.: standard deviation
Source: Based on author's own calculation

4.5 Selection of environmental variables

Based on the previous literature in efficiency of MFIs, four explanatory variables are considered. They are expected to best explain the variation of technical efficiency scores obtained in the first stage of the analysis. Following Gonzalez (2007), we design two variables such as Age (AGE) and legal type of the institution (TYPE) to capture the effects of MFIs' characteristics on financial and social efficiency estimates. We further include capital-to-assets ratio (EQAST) and return on assets (ROA) into the regression model to capture their influence on both dimensions of efficiency.

Age (AGE) of the institution can be taken as an indicator of the experience and managerial ability of the programs. The effect of age on technical efficiency can be twofold. According to Ledgerwood (1998), the efficiency improves as MFIs get mature. She argues that MFIs in early stage of their growing may have less efficiency due to higher operating costs. Evidence for this has been found by Paxton (2007) who concludes that institutional age is positively associated with technical efficiency. On contrary, in their analysis of outreach and efficiency of 450 MFIs in different countries, Hermes et al. (2011) reach different conclusions, finding older MFIs are less efficient. They further suggest that recently established MFIs may leapfrog the older institutions by acquiring the proven successful business model from the matured counterparts. Thus, the effect of AGE on efficiency of MFIs is not conclusive. TYPE is represented by a dummy variable and it takes the value of unity if the MFIs is registered as a NGO and zero otherwise. According to LMFPA (2012), NGOs in Sri Lanka extends their development goals into broad range while their counterparts, companies are restricted to a few selected development goals. Although equity funding is not very common, some NGO-MFIs receive equity fund in different degree from their promoter institutions and local investors. On the other hand, access to leverage varies from one institution to another. Thus, following Hermes et al., (2011), we include EQAST as a measure of the differences in risk taking by MFIs. The ratio is given by total equity over total assets of an MFI and it is in particularly useful for investors to decide if the MFIs financially sound to invest on. The previous studies to find the effects of EQAST on efficiency have concluded with paradoxical results: a considerable number of studies (eg: Dietsch & Lozano-Vivas, 2000; Girardone et al., 2004; Perera et al., 2007) reveal a positive effect. According to those findings, a lower capital ratio leads to lower efficiency levels because less equity implies a higher risk taken at greater leverage, which in turn results a greater borrowing cost. In contrast, some other studies (eg: Akhigbe & McNulty,2005; Dacanay, 2007; Sufian, 2009; Chan & Karim, 2010) find a negative effect of EQAST on the efficiency suggesting that accessing more debt relatively to the equity in financing banks result in higher efficiency as use of debt cause managers to manage the banks more cautious way as they are obliged to pay back the creditors. Thus, the effect of EQAST on efficiency is ambiguous (Sufian, 2009). In the present paper, we expect a negative correlation between EQAST and financial efficiency as equity investments are not common among unregulated MFIs in Sri Lanka (LMFPA, 2012). Consequently, they have to pay more attention to utilize leverage more efficiently in order to ensure the future borrowings. Finally, ROA is included as an explanatory variable as it gives some insight into the sustainability of MFIs (Hartarska, 2005; Mersland & StrØm, 2008). A caveat which should be outlined is that, as explained earlier, only unadjusted financial data are available.

We then use the following estimated specification to conduct separate truncated regressions for both financial and social efficiency measures.

$$\hat{\theta}^{*}_{i,t} = \beta 0 + \beta 1.AGE_{i,t} + \beta 2.TYPE_{i,t} + \beta 3.EQAST_{i,t} + \beta 4.ROA_{i,t} + \varepsilon_{i,t} \quad (3)$$

Where subscript i denotes a MFI and t time horizon and $\hat{\theta}^{*}_{i}$ is bias-corrected efficiency score of the i^{th} MFI (i=1,…,n), AGE indicates the operation years of an MFIs since its establishment, TYPE is a dummy variable that takes the value of 1 if it is a NGO, and zero if it is a company, EQAST is the total equity to total assets, ROA is the net profit before tax divided by total assets and ε is statistical noise. The bootstrap estimates are produced using 2000 bootstrap replications.

5. Empirical Results

5.1 First stage results: Financial and social efficiency measures

The results of the DEA bootstrap procedure described in the previous section are reported in Table 3. The first column indicates the name of MFI. The second column shows the original DEA efficiency estimate ($\hat{\theta}$), and third shows the bias-corrected estimate ($\hat{\theta}^{*}$). We then have the corresponding bootstrap bias estimate (BIAS) and the estimated confidence interval (LB = lower bound and UB = upper bound) for all MFIs. With regard to the original efficiency scores, two MFIs are financially efficient while six MFIs are deemed in socially efficient. On the other hand, bootstrap efficiency measures for both financial and social dimensions are concerned, none of the institution lie on the frontier. Moreover, Figure 1 and

Figure 2 contain the plots of original DEA scores, bias-corrected efficiency scores and 95 percent CI for both dimensions of efficiency. As can be seen, for both efficiency models, $\hat{\theta}$ remains outside the estimated CI suggesting that $\hat{\theta}$ over estimates the true efficiency of MFIs. $\hat{\theta}^{*}$ for both dimensions, however, are within the range of CI as bias correction is intended to correct for the derived bias. Hence, caution must be applied on benchmarking the performance of firms relying on conventional DEA estimates as ignoring the sample noise in the resulting efficiency estimators can lead to erroneous conclusions (Simar & Wilson, 2000).

Table 3

Financial and social efficiency scores under the CRS assumption: DEA with bootstrap

MFI	Financial Model					Social Model				
	$\hat{\theta}$	$\hat{\theta}^*$	BIAS	LB	UB	$\hat{\theta}$	$\hat{\theta}^*$	BIAS	LB	UB
1	0.4968	0.3907	0.1061	0.3218	0.4846	0.3932	0.3377	0.0555	0.2901	0.3857
2	0.1864	0.1381	0.0483	0.1163	0.1783	0.6757	0.5517	0.1240	0.4721	0.6540
3	0.1819	0.1515	0.0304	0.1246	0.1797	0.9631	0.8695	0.0936	0.7581	0.9466
4	0.3699	0.2543	0.1156	0.2182	0.3475	0.5412	0.4068	0.1344	0.3426	0.5191
5	0.4244	0.2817	0.1427	0.2393	0.3982	0.5777	0.4327	0.1450	0.3503	0.5656
6	1.0000	0.6398	0.3602	0.5579	0.8961	1.0000	0.7106	0.2894	0.5944	0.9634
7	0.3059	0.2641	0.0418	0.2200	0.3038	1.0000	0.8060	0.1940	0.7264	0.9608
8	0.4333	0.3400	0.0933	0.2790	0.4243	1.0000	0.7150	0.2850	0.6167	0.9538
9	0.2060	0.1712	0.0348	0.1417	0.2033	0.8656	0.7793	0.0863	0.6814	0.8503
10	0.7497	0.5729	0.1768	0.4842	0.7155	0.1508	0.1297	0.0211	0.1130	0.1487
11	0.8742	0.7364	0.1378	0.5994	0.8664	0.2840	0.2207	0.0633	0.1873	0.2754
12	0.2379	0.1863	0.0516	0.1568	0.2314	0.2775	0.2411	0.0364	0.2098	0.2724
13	0.3509	0.2863	0.0646	0.2352	0.3447	0.0998	0.0891	0.0107	0.0773	0.0985
14	0.2225	0.1774	0.0451	0.1470	0.2175	0.5667	0.5000	0.0667	0.4336	0.5573
15	0.5142	0.3587	0.1555	0.2999	0.4881	0.9099	0.7214	0.1885	0.5863	0.8908
16	0.1894	0.1518	0.0376	0.1247	0.1866	0.3811	0.3299	0.0512	0.2843	0.3740
17	0.2530	0.2029	0.0501	0.1679	0.2470	0.2604	0.2296	0.0308	0.2004	0.2556
18	0.1645	0.1247	0.0398	0.1060	0.1566	0.5020	0.4282	0.0738	0.3727	0.4931
19	0.2287	0.1702	0.0585	0.1448	0.2140	0.3469	0.2921	0.0548	0.2548	0.3408
20	0.2368	0.2020	0.0348	0.1667	0.2348	1.0000	0.8815	0.1185	0.7838	0.9620
21	0.3823	0.3267	0.0556	0.2716	0.3789	0.3775	0.3379	0.0396	0.3002	0.3676
22	0.2219	0.1869	0.0350	0.1555	0.2192	1.0000	0.8950	0.1050	0.7947	0.9744
23	0.2758	0.2121	0.0637	0.1765	0.2673	0.2481	0.2072	0.0409	0.1778	0.2413
24	0.3631	0.3011	0.0620	0.2518	0.3583	0.3464	0.3093	0.0371	0.2734	0.3372
25	0.2583	0.2199	0.0384	0.1830	0.2556	0.2082	0.1874	0.0208	0.1662	0.2044
26	0.2856	0.2404	0.0452	0.1950	0.2833	0.5195	0.4384	0.0811	0.3760	0.5065
27	0.6955	0.5605	0.1350	0.4561	0.6862	0.1658	0.1291	0.0367	0.1096	0.1593
28	1.0000	0.6839	0.3161	0.5715	0.9424	1.0000	0.7523	0.2477	0.6090	0.9561
29	0.0791	0.0591	0.0200	0.0489	0.0772	0.8433	0.7117	0.1316	0.5928	0.8329
30	0.2076	0.1628	0.0448	0.1362	0.2005	0.4642	0.4048	0.0594	0.3511	0.4570
31	0.5114	0.3920	0.1194	0.3231	0.4990	0.9773	0.8405	0.1368	0.7135	0.9657
32	0.1737	0.1414	0.0323	0.1160	0.1711	0.6382	0.5670	0.0712	0.4927	0.6298
33	0.1311	0.1099	0.0212	0.0910	0.1294	0.4984	0.4492	0.0492	0.3948	0.4887
34	0.4457	0.3251	0.1206	0.2758	0.4193	0.2633	0.2145	0.0488	0.1849	0.2544
35	0.1128	0.0805	0.0323	0.0665	0.1093	0.2016	0.1638	0.0378	0.1322	0.1990
36	0.2675	0.2038	0.0637	0.1712	0.2556	0.8367	0.7148	0.1219	0.6204	0.8189

Total number of iterations = 2000

Source: Based on author's own calculation

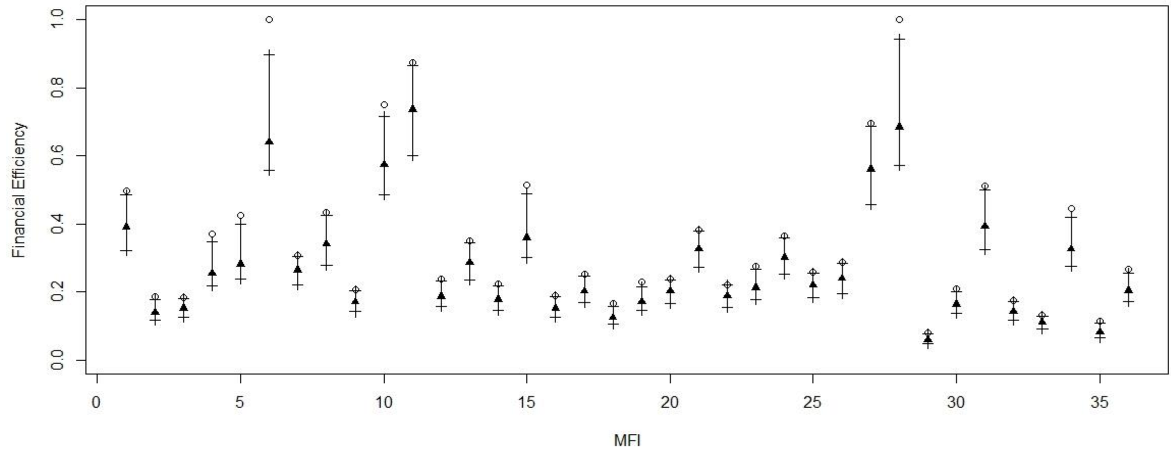

Figure 1. The graph of $\widehat{\theta}$ (o), $\widehat{\theta}^{*}$ (▲) and 95% CI for the financial model

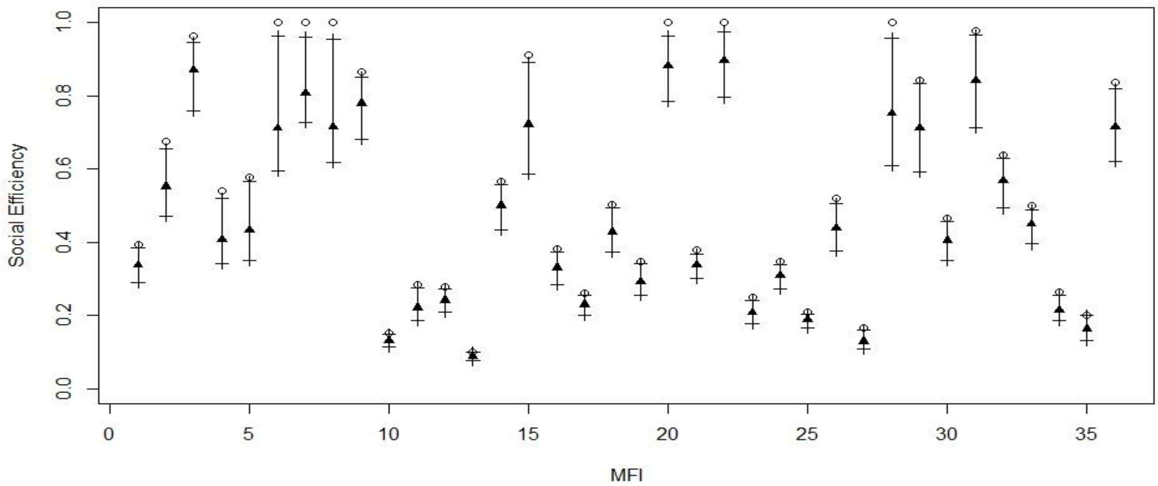

Figure 2. The graph of $\widehat{\theta}$ (o), $\widehat{\theta}^{*}$ (▲) and 95% CI for the social model

Additionally, Figure 3 presents a visual picture of the bias-corrected financial efficiency against the bias-corrected social efficiency measures. As can be seen in the scatter plot, a significant number of MFIs that are located at the bottom left corner are relatively ineffective along financial and social perspectives. However, several MFIs locate at the top left corner indicating that they perform relatively well on the social dimension but not on the financial aspects. A possible explanation for this may be that many NGOs that start with donor driven development projects use microfinance as one of the tools for achieving social objectives (LMFPA, 2012). On the other hand, given input and output specifications, none of the MFIs locates at the top right corner of the plot. Thus, none of the MFIs in our sample is simultaneously effective on both dimensions of efficiency. Finally, only one MFI (labeled as 11) locates at the bottom right corner corresponding for relatively efficient in financial terms, but it has not performed well on social dimension.

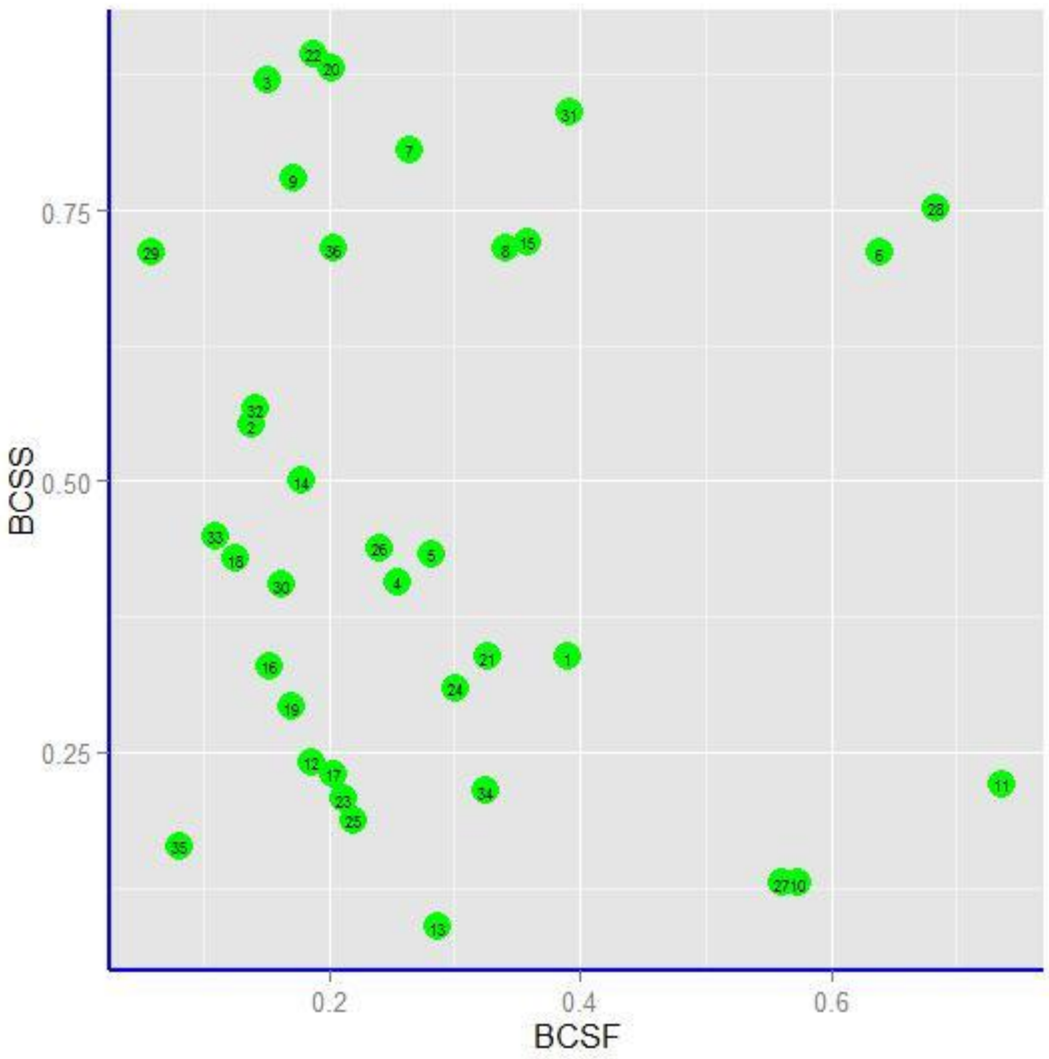

Figure 3. Scatter plot of the bias-corrected financial efficiency (BCSF) score versus the bias-corrected social efficiency (BCSS) score.

5.3 Second stage results: Factors accounting for efficiency variations

Table 4 presents the regression estimates for the financial and social models. The coefficient for AGE remains positive and significant with financial model indicating that matured MFIs have higher financial efficiency. This finding is consistent with Lebovics et al. (2014). In contrast, the effect of age on social efficiency is negative and significant suggesting that matured MFIs are relatively inefficient in social dimension. This may be a classical mission drift example (Mersland & Strøm, 2010): as MFIs gets older (and often larger), they tend to diversify their portfolio towards other types of customers than the initial target ones. The drift is often towards larger-size customers; in our case it is a gender shift. The coefficients for TYPE, the dummy variable indicates no influence on the financial efficiency. Nonetheless, the positive and significant coefficient for TYPE with the social models concludes that the NGOs are socially more efficient compared to the companies. While this second finding corroborates previous findings by Gutiérrez-Nieto et al. (2009) and is in line with our expectations, the first finding is at first surprising as the so-called companies are expected to perform better than their non-profit oriented peers. EQAST shows a negative and statistically significant relationship with financial efficiency suggesting that MFIs with lower equity to assets ratios tend to have higher financial efficiency measures. A possible explanation for this might be that more financially efficient MFIs use more leverage as the main source of their capital base. As a result, managers have to exploit the borrowed fund more carefully as they are obliged to pay them back. Moreover, because of less negotiated time and less intensive relationship with lender than with equity investors may result in a greater administrative efficiency for the MFIs (Maisch, et al. 2006). On the other hand, the coefficient concerning the relationship between EQAST and social efficiency is not significant suggesting that EQAST makes no effect on social efficiency. Finally, the coefficient for ROA is positively related to the financial efficiency. This is however insignificant and no statistical basis. Hence, our analysis does not catch any effect of ROA on the financial efficiency. In their analysis of MFIs in Vietnam, Lebovics et al. (2014) find a similar result and conclude that financial performance and financial efficiency do not necessarily go hand in hand. This coefficient, on the other hand, exhibits a negative and significant relationship with social efficiency model suggesting that more profitable MFIs tend to exhibit lower social efficiency which is in line with what described by Zeller & Meyer (2002) unless adequate solutions are applied to make financial sustainability, social impact and outreach consistent.

Table 4
Results of the second stage bootstrap truncated regressions

Variable	Financial Model	Social Model
Constant	1.7904	2.8918
AGE	0.1186**	-0.1612*
TYPE	1.4226	2.5644*
EQAST	-2.9504*	2.4194
ROA	1.3547	-16.4860*

Note: The dependent variables of financial model and social model are bias-corrected financial efficiency scores and bias-corrected social efficiency scores, respectively. (**), (*): Significant at the 5% level and at the 10% level, respectively; Total number of iterations = 2000

6. Conclusion

This paper examines the efficiency and its determinants of 36 MFIs in Sri Lanka. Two DEA models are constructed to capture the duel objectives of microfinance programs. The major contribution of the present paper is the use an innovative two stage double bootstrap DEA approach, where bias-corrected efficiency scores obtained using the homogeneous bootstrap method (Simar & Wilson, 2000) in the first stage of analysis, are used in the second stage double bootstrap truncated regression (Simar & Wilson, 2007). We extend our analysis in the second stage by investigating determinants of both dimensions of efficiency. The results of the second-stage analyses to identify the economic conditions that create inefficiency help MFIs to improve the managerial performance (Daraio & Simar, 2005). Moreover, the use of the double bootstrap method in the current study account for the bias and serial correlation of efficiency estimates. Thus, in contrast to the previous literature based on conventional DEA models, the results obtain in the present paper is more meaningful.

Results from the first stage show that MFIs that are deemed in fully efficient as indicated by original efficiency estimates become less efficient when applying the bias-corrected method. This inconsistency between original efficiency and bias-corrected efficiency scores can be explained by the fact that original efficiency scores are based on the conventional DEA that fails to account for the measurement error in the estimation of efficiency. Hence, the benchmarking of MFIs relying on the original efficiency scores may be misleading. Furthermore, when observing the bias-corrected efficiency estimates, we realize that none of the MFIs performs well on both financial and social dimensions. Although some MFIs perform well on social dimension, none are effective on the financial dimension except one. A significant number of MFIs are inefficient in both dimensions. From this analysis, it emerges, as a general suggestion, that MFIs that are inefficient in both dimensions and efficient in only one dimension should work on the weaknesses and restructure their policy choices to simultaneous improvement of both dimensions of efficiency. This is not an easy task, as the triangle of microfinance (Zeller and Meyer, 2002) clearly depicts. In order to make consistent choices, knowing the driver of performance is a preliminary step. Based on relevant literature, some factors are considered more likely to explain these performance. The second part of the paper set out to determine the effect of age of the intermediary (AGE), its institutional type (TYPE), the degree of capitalization (equity/assets, EQAST) and an indicator of profitability (measured by the ROA) on both dimensions of efficiency. The results reveal that AGE and EQAST are significantly influential on the financial efficiency. This confirms that, while many MFIs find it difficult to reach the break-even in their early stages, time allows to increase the size and to better manage the processes in order to achieve profitability. Again, an interesting finding is that those MFIs that are more financially exposed, tend to perform better to keep attracting their lenders, a positive incentive effect. The insignificant effect of ROA on profitability may be attributed to the limits of measuring profitability without applying the adjustments suggested by analysts to consider, among other things, the subsidies. On the other hand, AGE, TYPE and ROA have significant effect on social efficiency. The older MIFs appear to be affected by some mission drift effect, while, as expected, NGO-type MFI are more socially oriented. The ROA has an expected effect on efficiency as it appears that more social action erodes profitability. A challenge, in fact, for MFIs of any type is to find ways of making a successful social performance consistent with a satisfactory financial performance. Therefore, as this study offers on the various factors affecting both performance, it contributes to a deeper awareness of potential directions for future action in this respect.

In general, this study could help MFIs to make strategic decisions to compete in the dynamic market. The underperformers could look at their peers who are successful and try to follow the business plans of market leaders of the same type, while also learning from MFIs of different institutional type and try to adjust their strategies. This means, as an example, that while NGO may probably benefit from leading financial strategies of successful commercial NGOs, the former could learn from socially successful NGO how to foster their social performance.

The study may also be helpful to donors and Governments who should be led to use both dimensions of performance of MFIs in the criteria to reward MFIs and allocate funds for their support and promotion. From the policy point of view, the results provide useful information for policymakers to implement appropriate regulatory mechanisms to streamline the performance of MFIs in Sri Lanka.

The main limitation of the current study is that our analysis is based on the cross-sectional data for one year and thereby, it does not capture the productivity changes of MFIs. Thus, future investigation of changes in productivity over a stretch of time as a result of technical change or technological progress (or decline) using the Malmquist bootstrapped index could be a logical extension to the present paper. Another limitation, on the financial efficiency side, is the use of non-adjusted profitability indicators. The adjustment of data would be possible only by obtaining the relevant information by the individual MFIs. On the efficiency side, the use of gender orientation as a proxy for social performance could be strengthened by adding other indicators of other dimensions of social performance.

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Productivity change of microfinance institutions in Kenya: a bootstrapped Malmquist approach

Abstract

This paper uses a DEA based bootstrapped Malmquist method to investigate the changes in productivity of 20 Kenyan microfinance institutions (MFIs) over the period 2009-2012. Productivity change is further decomposed into changes in technology, pure efficiency and scale efficiency. The results indicate that MFIs have experienced about 7% annual productivity progress on average, which is mainly attributable to technological improvements over the considered period. A second stage bootstrapped regression analysis is employed to examine the impact of several environmental variables on productivity change measures. Results show that matured MFIs tend to have a lower productivity compared to the younger counterparts. In addition, the results indicate that return on assets associates positively with both productivity and technological progress. Bootstrap methods employed in the paper help to tackle the statistical limitations of the conventional DEA methodology. While the present paper focuses on Kenyan microfinance industry, the policy implications derived can also be applicable to MFIs operate elsewhere with similar socio-economic characteristics.

1. Introduction

Over the past few years, Microfinance Institutions (MFIs) have gone through sweeping changes, mainly driven by rapid innovations in technology and introduction of supportive policy reforms, which in turn have considerably altered the environment on which they operate. The diffusion of information and communication technology (ICT) applications such as promoting of mobile phone based money transactions, automated teller machines (ATMs), online remittance and utility bill payment facilities have enabled many MFIs to improve the financial inclusion in a cost effective way. Moreover, investing in ICT helps MFIs to secure their survival in a more competitive environment while achieving benefits similar to those for commercial banks entertaining such as better operational efficiency and risk management (Kauffman & Riggins, 2012). On the other hand, the implementations of appropriate policy initiatives have helped a number of credit-only MFIs to slash the overall costs of inputs by transforming into full-fledged formal financial institutions that are able to offer range of financial services including savings mobilization (Balkenhol, 2007).

The advances in technology and implementation of new policy instruments that ensure the systemic stability and client protection (Arun, 2005) have spurred the competition among MFIs that operate in different niche markets. The growing competition has resulted in pushing the production possibility frontier outward, increasing the outreach and sustainability that can be achieved (Manso & Yaron, 2009). Although several studies (eg: Nghiem et al., 2006; Gutiérrez-Nieto et al., 2007; Gutiérrez-Nieto et al., 2009; Hermes et al., 2011; Servin et al., 2012: Piot-Lepetit & Nzongang, 2013) have been conducted to measure the efficiency of MFIs using cross-section data from a particular year, these studies still fail to account for the frontier shift over time. Despite the importance of studying the shifts in the frontier of MFIs in response to changes in regulatory and technological environment, empirical literature on productivity moments of MFIs is still in its infancy. This may indicates the greater difficulty of finding time series data for individual MFIs.

This study aims to quantify the Malmquist index and its components of 20 MFIs operate in Kenya over the four year period from 2009 to 2012 (80 observations). The microfinance industry in Kenya is of particular interest to investigate the productivity growth as it goes through strong regulatory changes and technological advances in recent years. In an effort to streamline the microfinance industry in Kenya, the Microfinance Act was enacted in 2006 and became operational in 2008. The Act provides directions for MFIs to strengthen the corporate governance principles, safeguard the depositors, adherence to core capital requirements, promote competition to enhance efficiency and conduct the business in a prudent and professional manner (DPFB, 2013). The Financial Act of 2010 amends the Banking and Microfinance Act to allow Deposits-Taking Microfinance Institutions (DTMs) to use of agents to conduct deposit taking business in view of improving financial inclusion in frontiers in rural areas (Central Bank of Kenya, 2011). The Banking and Microfinance Act was further amended through Finance Act 2012 to require all institutions licensed under the two statutes to share credit information through credit reference bureaus with the aim to growth of the credit market (Central Bank of Kenya, 2012). Moreover, several successful transformations of non-governmental microfinance providers into regulated deposit taking financial institutions have taken place in Kenya. Transformation of Equity Building Society into Equity Bank and transformation of Kenya Rural Enterprise program into K-Rep Bank are among such successful episodes (see Ledgerwood & White, 2006). In addition, several credit-only MFIs were granted the deposit taking license under the Microfinance Act 2006 to transform into DTMs. On the other hand, Kenya, where the mobile banking revolution originated (Graham & Nikolova, 2013), has demonstrated the best use of technology for improving the financial inclusion (Gwalani & Parkhi, 2014). The recent development in mobile phone technology has enabled a large number of people who are otherwise excluded from formal financial institutions to access a range of financial services at low costs. For example, according to Demombynes & Thegeya (2012), 93% of people in Kenya are mobile phone users and 73% are mobile money customers by 2012. Thus, mobile money is ubiquitous in Kenya (Vaughan et al. 2013). Especially, the introduction of M-PESA money-transaction service in 2007 has made a dramatic impact on Kenyan financial landscape over the years (Johnson & Arnold, 2012; Assunção, 2013). Apart from financial inclusion, M-PESA money-transfer program may also enhance the agency and well-being of people (Graham & Nikolova, 2013). IMF (2011) reveals that M-PESA provides mobile banking services to more than 70% of Kenyan population, and it processes more transaction within Kenya than Western Union does globally. It is therefore interesting to investigate how Kenyan MFIs react in response to these recent changes in regulatory and technological environment in order to secure their survival.

In the current study, we use Data Envelopment Analysis (DEA) based Malmquist productivity index (Färe et al., 1994) to measure the productivity of MFIs. Since it requires neither any price data nor any specific behavioral assumption such as cost minimization or profit maximization (Coelli et al, 2005), it becomes a suitable method towards measuring the changes in productivity in the microfinance context. For example, in some cases, the price data of MFIs may be distorted due to states interventions or due to bad accounting practices. In addition, behavioral assumption of MFIs may difficult owing to the problem of duel maximization (Rhyne, 1998). An additional advantage of the Malmquist index (MI) is that decomposition of it into efficiency change ("catching-up") and technological change ("innovation") sheds light on the sources of productivity movements in MFIs over the period concerned. Yet the DEA based Malmquist productivity index has been criticized for not accounting for the measurement errors in the estimation of Malmquist indices, with possible consequence for erroneous policy conclusions. Simar & Wilson (1998, 1999, 2000) based on the bootstrap concept (Efron, 1979) attempt to remedy this drawback by proposing a DEA bootstrapping method that analyses the sensitivity of measured efficiency scores to the sampling variation of the estimated frontier. Simar & Wilson (1999) further extend the bootstrap method by introducing bivariate smoothing procedure to preserve any temporal correlation present in the data. Thus, the present paper for the first time employees the bootstrap Malmquist approach proposed by Simar & Wilson (1999) to obtain confidence intervals for the Malmquist index and its components to determine whether the changes are statistically significant. Additionally, in line with Odeck (2009) and Assaf (2011), we employ a second-stage truncated bootstrap regression (Simar & Wilson, 2007) to explain the variations in total factor productivity (TFP) and technological changes (TEC) of MFIs in terms of several environmental variables.

From methodological points of view, the main contribution of the present paper lies in the use of bootstrap DEA Malmquist proposed by Simar & Wilson (1999) and subsequent truncated regression with bootstrap approach proposed by Simar & Wilson (2007) in the second stage analysis. As for an additional contribution, in comparison to the earlier studies with Mix Market data that are self-reported and consequently skewed towards MFIs that have stressed financial objectives and profitability (Cull et al., 2011), we use subsidy adjusted high quality balance panel data set executed from rating reports. To the best of the author's knowledge, this is the first attempt to investigate the productivity changes of MFIs using a bootstrap method.

Our results suggest that Kenyan MFIs have experienced about 7% annual productivity progress on average, which is mainly attributable to technological improvements over the period 2009 – 2012. Moreover, the second-stage regression results reveal that matured MFIs tend to have lower productivity compared to the younger ones that have been putting more effort into innovative business strategies. We also find that higher return on assets (ROA) associate with the productivity gain and technological advances over the considered period.

The findings of the present paper can be used by managers and policy makers to reassess the success and failures of the current policy choices. Since the implementation of several important regulatory changes falls within the study period, results of this study provide important insight into their impacts on the productivity change. Moreover, the results that are significant in statistical sense help managers to make more effort to improve the performance of the institutions that are desperately needed the improvements (see Löthgren & Tambour, 1999).

The rest of the paper unfolds as follows. The next section provides a brief literature review. Section three discusses the methodology and data specification of input and output variables employed. Section four presents the empirical results. Section five concludes.

2. Literature review

There are several studies that investigate the efficiency and productivity of MFIs. They rely on the use of either parametric methods like Stochastic Frontier analysis (SFA) or non-parametric Data Envelopment Analysis (DEA) technique. Appendix (A) presents a survey of previous research conducted to investigate efficiency and productivity of MFIs using these frontier methodologies.

Paxton (2007) use the SFA to examine the 190 semiformal financial institutions in Mexico and discovers that technology, average loan size, rural outreach and the age of institution are all positively associated with technical efficiency. Heremes et al. (2008) examine the possible trade-off between depth of outreach and efficiency of MFIs by applying SFA. The results show that outreach is negatively related to the efficiency. By employing

SFA, Servin et al. (2012) analyze the technical efficiency of 315 MFIs operating in 18 Latin American countries. Their results suggest that differences in efficiency are associated with the differences in ownership types (i.e. NGOs, cooperatives and credit unions, NBFI, and banks).

Gutiérrez-Nieto et al. (2007) examine the efficiency of 30 MFIs in Latin America. They show that efficiency is affected by country effects and by regulatory status (i.e., NGO or non – NGO status). Bassem (2008) use DEA to measure the efficiency of 35 MFIs in Mediterranean zone. He shows that size of MFIs has a negative effect on efficiency. Gutiérrez-Nieto et al. (2009) and Piot-Lepetit & Nzongang (2014) incorporate financial and social output measures in separate DEA models to assess the performance of MFIs from both financial and social perspectives. Gutiérrez-Nieto et al. (2009) apply DEA to a sample of 89 MFIs and find a positive correlation between outreach and sustainability. They also emphasize the importance of assessing social efficiency of MFIs. Piot-Lepetit & Nzongang (2014) use DEA to find whether trade-off exists between outreach and sustainability of 52 MFIs in Cameroon. They find mix results. Nghiem et al. (2006) conducts two stage analyses. First, they obtain efficiency scores for each 44 MFI in Vietnam using DEA technique. Then, in a second stage, the efficiency scores obtained in the first stage of the analysis are regressed on a set of potential environmental variables. They reveal that age and the location of MFIs are determinants of efficiency. Among the handful of studies attempting to evaluate productivity changes of MFIs, Bassem (2014) examines productivity changes in 33 MFIs operate in Middle East and North African (MENA) region during the period 2006 – 2011 using DEA based Malmquist productivity index and finds that overall productivity decline in MENA region during this period. However, methodology employed in the study has a shortcoming as it does not take into account the uncertainty surrounding the estimates of MI and its components due to sampling variation. Thus, it is not possible to determine whether the results indicate real change in productivity or outcome of sampling noise.

The present paper extends the literature discussed above. We investigate the productivity change in 20 Kenyan MFIs over the period 2009-2012, using the DEA Malmquist bootstrap method (Simar & Wilson, 1999). The decomposition of Malmquist index into changes in efficiency and technology helps us to separate their contribution in productivity change. Moreover, the bootstrap method applied in the present paper allows us to obtain measures of statistical precision in the estimates. Additionally, we employ a second-stage truncated bootstrap regression (Simar & Wilson, 2007) to explain the impact of several environmental variables on TFP and TEC.

3. Methodology

3.1. The Malmquist Index

The Malmquist productivity index, introduced by Caves et al. (1982) using input and output distance functions and further extended by Färe et al. (1992), is a widely used method to measure the changes in productivity of various firms. The present paper employees the output-oriented Malmquist productivity index ($\mathrm{MI_o}$) assuming that managers of MFIs attempt to maximize output from a given set of inputs. Consider a number of j = (1,…,J) MFIs operate over t = 1,…,T time period using n inputs to produce m outputs. The production technology in time period t ($\mathrm{S^t}$) is written as:

$$\mathrm{S^t} = \{(\mathrm{x^t}, \mathrm{y^t}): \mathrm{x^t}\text{can produce } \mathrm{y^t}\} \qquad (1)$$

Where $x^t \in R_+^n$ and $y^t \in R_+^m$ are input and output vectors.

Following Shepard (1970) and Fare et al. (1994), the output distance function at time t is defined as:

$$D_o^t(x^t, y^t) = inf\{\theta: (x^t, y^t/\theta) \in S^t\} \quad (2)$$

Where D_o denotes the output-based distance function.

To define the Malmquist index, Fare et al. (1994) use distance functions in two different time periods, t (the base period) and t+1 as follows:

$$D_o^t(x^{t+1}, y^{t+1}) = inf\{\theta: (x^{t+1}, y^{t+1}/\theta) \in S^t\} \quad (3)$$
$$D_o^{t+1}(x^t, y^t) = inf\{\theta: (x^t, y^t/\theta) \in S^{t+1}\} \quad (4)$$

Following Fare et al. (1994), $\mathrm{MI_o}$ for each MFI between t and $(\mathrm{t}+1)$ is defined as the geometric mean of two Malmquist productivity indices as shown in equation (5).

$$MI_o^{t,t+1} = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} X \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right]^{1/2} \quad (5)$$

Where the components inside the brackets are the output-based Malmquist productivity indices defined by the Caves et al. (1982). The first component is measured with respect to period t technology and the second component is measured with respect to period $t+1$ technology. A value of $\mathrm{MI_o}$ greater than 1 denotes productivity progress, $\mathrm{MI_o}$ less than 1 indicates productivity decline and $\mathrm{MI_o}$ equal 1 represents no productivity change between period t and $t+1$.

Fare et al. (1994) demonstrates that the $\mathrm{MI_o}$ in equation (5) can be decomposed into changes in technical efficiency and changes in frontier technology as follows:

$$MI_o^{t,t+1} = \frac{D_o^{t+1},(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} X \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} X \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right]^{1/2} \quad (6)$$

Where the ratio outside the brackets measures the efficiency change between time period t and t+1 and the geometric mean of the two ratios inside the bracket measures the shift in the production frontier between two time periods.

Following Fare et al. (1994), efficiency change in equation (6) is further disentangled into pure efficiency change and scale efficiency change as follows:

$$\text{Efficiency change} = \underbrace{\frac{D_{VRS}^{t+1}(x^{t+1},y^{t+1})}{D_{VRS}^{t}(x^{t},y^{t})}}_{\text{Pure Efficiency Change}} X \underbrace{\frac{D_{CRS}^{t+1}(x^{t+1},y^{t+1})/D_{VRS}^{t+1}(x^{t+1},y^{t+1})}{D_{CRS}^{t}(x^{t},y^{t})/D_{VRS}^{t}(x^{t},y^{t})}}_{\text{Scale efficiency change}} \qquad (7)$$

Where D_{CRS} denotes the output distance function for constant returns to scale (CRS) and D_{VRS} represents the output distance function for variable returns to scale (VRS). For MI and its components, values greater than one indicate a progress whereas values less than one indicate a regress.

In order to calculate the Malmquist index estimate and its decompositions in equation (6) and (7), four different DEA linear-programming problems need to be solved. Assuming J is the number of MFIs that produce M outputs by using N inputs, the linear programming problems to be solved for jth MFI (j = 1,…,J) can be stated as follows:

$$\begin{aligned} \left[D_o^{t+1}\left(x_j^{t+1}, y_j^{t+1}\right)\right]^{-1} &= max_{\theta,\lambda}\theta, \\ st \qquad -\theta y_j^{t+1} + Y^{t+1}\lambda &\geq 0, \\ x_j^{t+1} - X^{t+1}\lambda &\geq 0, \\ \lambda &\geq 0 \end{aligned} \qquad (8)$$

$$\begin{aligned} \left[D_o^{t}\left(x_j^{t}, y_j^{t}\right)\right]^{-1} &= max_{\theta,\lambda}\theta, \\ st \qquad -\theta y_j^{t} + Y^{t}\lambda &\geq 0, \\ x_j^{t} - X^{t}\lambda &\geq 0, \\ \lambda &\geq 0 \end{aligned} \qquad (9)$$

$$
\begin{aligned}
&\left[D_o^{t+1}\left(x_j^t, y_j^t\right)\right]^{-1} = max_{\theta,\lambda}\theta, \\
&st \qquad -\theta y_j^t + Y^{t+1}\lambda \geq 0, \\
&\qquad x_j^t - X^{t+1}\lambda \geq 0, \\
&\qquad \lambda \geq 0
\end{aligned}
\tag{10}
$$

$$
\begin{aligned}
&\left[D_o^{t}\left(x_j^{t+1}, y_j^{t+1}\right)\right]^{-1} = max_{\theta,\lambda}\theta, \\
&st \qquad -\theta y_j^{t+1} + Y^{t}\lambda \geq 0, \\
&\qquad x_j^{t+1} - X^{t}\lambda \geq 0, \\
&\qquad \lambda \geq 0
\end{aligned}
\tag{11}
$$

Where θ is a scalar, λ is a vector of constant. Note that solution of two additional linear-programming problems such as $D_o^t\left(x_j^t, y_j^t\right)$ and $D_o^{t+1}\left(x_j^{t+1}, y_j^{t+1}\right)$ with VRS assumption is required to derive the pure technical efficiency and scale efficiency measures in equation (7). See Fare et al. (1994) and Coelli et al. (2005) for more details on linear-programming problems.

3.2. Bootstrapping Malmquist indices

Though DEA is very flexible and requires no restrictive assumptions about the analytical form of the production function, it still suffers from some limitations. One of the serious disadvantages is that DEA estimates are subject to uncertainty due to sampling variation (Simar & Wilson, 2000). Since, the estimation of productivity, efficiency and technological changes in equations (6 and 7) are based on conventional DEA, it is not clear whether these estimates indicate real changes or are artificial of sampling noise (see Simar & Wilson, 1999). The bootstrap procedure proposed by Simar & Wilson (1998, 1999, 2000) overcomes this limitation. The basic idea behind the bootstrap technique is to resample from the original data set to construct a "pseudo" sample to make inference on the parameters of interest. The bootstrap procedure (Simar & Wilson, 1998) is further extended by Simar & Wilson (1999) to the case of Malmquist indices constructed from DEA using time series data set. They propose a bivariate smoothing procedure to preserve possible temporal correlation present in data. Thus, following Simar & Wilson (1999), we obtain the bootstrap estimates and confidence intervals for the Malmquist indices of each MFI. The confidence intervals yielded are then used to hypothesis testing to determine whether the changes are significant in a statistical sense. See Simar & Wilsn (1998, 1999, 2000) for technical details on bootstrap algorithm employed in the present paper. Also, see Tortosa-Ausina et al., (2008); Assaf, (2009) & Odeck (2009) for step-by-step demonstration of bootstrap algorithm. The present study performs 2000 bootstrap iteration (B = 2000).

3.3 Variables and data

The data used in this study are drawn from AMFI (2012 & 2013). The data consists of 20 MFIs over the period of 2009-2012 (80 observations). All MFIs on which data existed in consistent basis for the entire period are included. All the financial data are in terms of United States Dollars (US$), unless otherwise state. In the present paper we use three input and two output variables. The selection of these variables is influenced by literature on DEA applications in microfinance programs as summarized in Appendix A. The summary statistics of the variable used are reported in Table 1. We select total assets, operating expenses and labor as input variables which have commonly been used in earlier studies. The total assets are defined as the total of all net assets. Operating expenses are expressed as expenses related to operations. Labor is proxied by number of employees. In order to link output variables to the duel objectives of microfinance programs, we select revenue and total number of active borrowers as output measures. Revenue captures the financial performance of MFIs. Number of active borrowers, on the other hand, is a proxy for the breadth of outreach. See Schreiner (2002) for a discussion on outreach indicators.

Table 1
Descriptive statistics of input and output variables, 2009 – 2012

Variable	Year	Mean	Std.dev.	Minimum	Maximum
Total Assets*	2009	85,090	283,415	77	1,272,909
	2010	107,631	368,921	270	1,658,040
	2011	128,816	461,719	414	2,079,639
	2012	155,347	557,015	781	2,509,616
Operating expenses*	2009	8,681	23,223	18	103,121
	2010	10,204	28,167	32	125,718
	2011	12,305	36,753	76	164,946
	2012	13,965	40,170	47	179,498
Staff	2009	405	974	9	4,291
	2010	445	1,097	9	4,809
	2011	508	1,272	9	5,565
	2012	555	1,377	7	6,030
Revenue*	2009	11,506	32,676	3	144,042
	2010	12,800	36,850	7	162,694
	2011	17,302	54,906	47	246,780
	2012	23,629	75,632	69	339,870
Active borrowers	2009	68,356	169,826	156	715,969
	2010	63,500	148,434	199	619,561
	2011	67,599	168,654	206	744,544
	2012	70,243	176,005	247	781,604

Note:* denotes thousand of United States Dollars
Source: AMFI, (2012 & 2013)

4. Empirical Results

The results are obtained by using the Malmquist productivity formulation and solving the linear programming models discussed in preceding paragraphs. MI is decomposed into technical efficiency change (EFFIC) and technological change (TEC). EFFIC implies the diffusion of technology (Alam, 2001) whereas TEC refers to changes in the best practice production frontier (Nishimizu & Page, 1982). EFFIC is further dismantled into pure efficiency change (PEC) and scale efficiency change (SEC). Calculated confidence intervals for changes in MI and its components are used to determine if these changes are statistically significant. The confidence intervals yielded (i.e., 99%, 95% and 90%) are used to test the null hypothesis. The null hypothesis of statistically insignificant changes in productivity, efficiency and technology, respectively, is that the corresponding measures are not statistically significant. For example, if the 99% (95%, 90%) confidence interval includes the value one, then the corresponding measure (i.e., MI, EFFIC, TEC, PEC and SEC) is not significantly in statistical sense at 1% (5%, 10%) level. However, if the confidence interval does not include the value one, then the corresponding measure is statistically significant.

Table 2 illustrates the changes in productivity, technology, efficiency, pure efficiency and scale efficiency for each MFI between 2009 and 2012. The value of index greater than one denotes a progress whereas the value less than one denotes a regress. Index value equals to one indicate no change. Three asterisks (***) are used to denote that indices are significantly different from one at the 0.01 level. Similarly, double asterisks (**) and single asterisks (*) indicate that indices are significantly different from one at the 0.05 and 0.1 levels respectively. The disaggregated results are not included to preserve the space, but can be provided upon request.

It is apparent from the Table 4 that 11 MFIs have a significant TFP increase during the period 2009 – 2012, of these 5 MFIs are significant at the 1% level, and the remainders are at the 5% level. On the other hand, 2 MFIs have a significant TFP decrease, each at the 1% and 10% levels. The changes in TFP of remaining 7 MFIs are not statistically significant. It is interesting to note that the two institutions (i.e., KWFT & SMEP) that have experienced a significant productivity regress are transformed from credit-only microfinance institution status to deposit-taking microfinance institutions legal type in year 2010. The decrease in productivity of these two institutions is caused by the significant decrease in their efficiency. Moreover, this regression may also be due to the fact that transformation entails a considerable amount of financial and human resources (see Ledgerwood & White, 2006).

When looking at the sources of productivity gain, we find that changes in technology is greater than unity for all MFIs over the sample period, of these 9 MFI have a significant technological progress (1 MFI is at 1%, 5 MFIs are at 5% and 3MFIs are at 10% levels).Thus, it seems that productivity growth of MFIs during this period mostly caused by the technological advances. This result is supported by the findings of FinaAccess (2013) that reports an increased penetration of mobile phone based money transactions between 2009 and 2013 in Kenya. Moreover, our findings reveal that EFFIC is less than unity for 14 MFIs, of which 4 MFIs have a significant regression (at 5% and 10% levels). A similar trend emerges in the PEC and SEC. In terms of PEC, 2 MFIs have a significant regression, each at 5% and 10% levels. The changes of pure efficiency for remaining institutions are not statistically significant. With respect to SEC which indicate the moments toward or away from constant-returns-to-scale-operation (Alam, 2001), 4 MFIs have experienced a significant regression (at 1%, 5% and 10% levels). It is therefore likely that regression in catching-up as a result of pure technical inefficiency and scale inefficiency.

Table 2
Productivity changes for each MFI between 2009 and 2012 (2000 iterations)

MFI	MI	TEC	EFFIC	PEC	SEC
AAR Credi Services	1.2147***	1.2147	1.0000	1.0000	1.0000
Bimas	1.0492***	1.0791	0.9723	1.0182	0.9550
ECLOF Kenya	0.9990	1.1032	0.9055	0.9707	0.9329
Equity Bank	1.1085***	1.1684**	0.9487	1.0000	0.9487
Faulu	1.0637**	1.0891	0.9767	1.0041	0.9727
Jamii Bora	1.0336	1.1685***	0.8846	0.9916	0.8921
Jitegemea Credit Scheme	1.0005	1.1291	0.8862	0.9739	0.9099***
Juhudi Kilimo	1.0906**	1.1648**	0.9362	0.9810	0.9544**
K-Rep	1.1824***	1.1788*	1.0031	1.0272	0.9765
Kadet	0.9938	1.1364*	0.8745*	0.9523	0.9184
KEEF	1.2250**	1.2250	1.0000	1.0000	1.0000
KWFT	0.9399***	1.0770	0.8728*	1.0000	0.8728
MicroAFRICA	1.1380**	1.1032	1.0315	1.1112	0.9282*
Opportunity Kenya	0.9913	1.0553	0.9393	0.8971*	1.0470
PAWDEP	1.1451**	1.1752	0.9744	1.0000	0.9744
SISDO	0.9660	1.1292**	0.8555**	0.8500**	1.0065
SMEP	0.9772*	1.1137*	0.8774**	1.0025	0.8752*
SUMAC Credit	1.0036	1.0563	0.9502	0.9238	1.0286
TAIFA Option Microfinance	1.2236**	1.2513**	0.9779	1.0000	0.9779
YEHU	1.1124***	1.1814**	0.9416	0.9639	0.9768
Geometric Mean	1.0693**	1.1387*	0.9390	0.9820	0.9562

***,**,* indicate significant differences from unity at 1% , 5%, & 10% confidence level respectively

4.1 Second stage regression analysis

Once the malmquist indices are calculated, the bootstrap truncated regression approach proposed by Simar & Wilson (2007) is used to determine the effects of age (AGE), initial efficiency (IEFFI) and ROA on MI and TEC. Although, Tobit model is widely used in the second stage analysis, Simar & Wilson (2007) highlight two main problems with such conventional regression models. First, they point out that the efficiency or productivity scores estimated in the first stage are likely to be biased in finite samples. Second, the efficiency or productivity scores are not independent observations as the estimation of the efficiency for one Decision Making Unit (DMU) incorporates all other DMUs in the sample. Consequently, the error term is serially correlated and standard methods to inference are invalid. Thus, the present study employees the bootstrap procedure proposed by Simar & Wilson (2007) to overcome the above limitations. See Simar & Wilson (2007) for a detailed discussion about the limitations of conventional regression models and bootstrap algorithm.

AGE is measured based on the number of years an MFI is in existence. Consistent with the study of Odeck (2009), efficiency scores for the base year (IEFFI) is included as productivity growth is conditional on the initial level of efficiency from which change occurs. In the analysis, we examine if initial efficiency is low in the base year, what effect does that have on the productivity and technological progress. In addition return on assets (ROA) is included as an indicator of sustainability of MFIs (Hartarska, 2005). It measures how effectively MFIs generate earnings from their investments.

The estimated specifications are as follows:

$$MI_{i,t} = \beta_0 + \beta_1 AGE_{i,t} + \beta_2 IEFFI_{i,t} + \beta_2 ROA_{i,t} + \varepsilon_{i,t} \quad (13)$$

$$TEC_{i,t} = \beta_0 + \beta_1 AGE_{i,t} + \beta_2 IEFFI_{i,t} + \beta_2 ROA_{i,t} + \varepsilon_{i,t} \quad (14)$$

Where, $MI_{i,t}$ and $TEC_{i,t}$ refer to total factor productivity and technological change, respectively. AGE refers to the operating years of an MFI since its establishment. IEFFI is the initial efficiency. ROA measures the financial performance of MFIs. $\varepsilon_{i,t}$ is the error disturbance.

Table 5 presents the results of regression analysis. AGE contributes negatively to TFP, suggesting that matured MFIs tend to have lower TFP compared to the younger MFIs. This finding is consistent with the view that as firms age, they become less able to respond to new challenges and succumb to the innovative competitors and thereby they may become less productive (see Barron et al. 1994). Our assumption of technological advancement of younger MFIs to improve TFP is further evident by the negative impact of AGE on TEC.

This results reflects that younger MFIs are more innovative compared to the matured. In other words, the negative impact of AGE on both TFP and TEC suggests that younger MFIs find it easier to implement productivity improvements and technology and being smaller like growth in percentage terms they are able to grow outputs faster. MI and TEC, however, do not have a statistically significant relationship with the initial efficiency, suggesting that initial efficiency has contributed to changes in neither TFP nor technology of Kenyan MFIs during the considered period. Finally, ROA has a positive and significant impact on TFP growth. The positive impact of ROA on TFP growth indicates that MFIs with greater financial performance may associate with higher TFP growth. Moreover, ROA associate positively with TEC, signifying that more profitable MFIs are more likely to invest in innovations.

Table 3. Truncated bootstrap regression (2000 iterations)

Variable	Coefficient	
	MI	TEC
(Constant)	1.1286 (0.0956)	1.1841 (0.0834)
AGE	-0.0060*** (0.0020)	-0.0025* (0.0015)
IEFFI	0.0302 (0.1169)	-0.0124 (0.1004)
ROA	0.0072** (0.0034)	0.0044* (0.0031)

Standard error in parentheses.
***,**,* denote significance at the 1% , 5%, & 10% levels, respectively.
Dependent variables are Malmquist index (MI) and technological change (TEC)

5. Conclusion

This study set out with the aim of assessing the productivity changes of MFIs in Kenya from 2009 to 2012. The decomposition of MI into pure efficiency, scale efficiency and technological change sheds light on the sources of productivity changes. The major contribution of the present paper is the use of bootstrap Malmquist index methodology proposed by Simar & Wilson (1999) to obtain confidence intervals for the Malmquist indices to determine whether the results indicate real change or is an artifact of sampling noise. In addition, use of the truncated regression with bootstrap in the second stage of the analysis helps to find possible determinants of TFP and TEC. The bootstrap techniques used ensure the robustness of findings.

The empirical results reveal that productivity of significant number of MFIs increases over time, with an average growth rate of about 7%. The most interesting finding to emerge from this study is that shift in the production frontier is the driven force of productivity gain over the period 2009 – 2012. Application of innovative financial instruments such as mobile phone based transactions and branchless banking services may be the root cause for the positive shift in the production frontier. The growth of productivity may also be attributed to the recent policy reforms that allow DTMs to use of agents to increase their distribution network as well as sharing of credit information with credit reference bureaus to minimize credit risk. It is also worthwhile to note that two MFIs have experienced a productivity regression. Both institutions are transformed from credit only MFIs into DTMs in years 2010. Thus, one possible reason for this decline is the pre and post transformations costs associated with the transformation process. Significant efficiency decline of both institutions may also indicate the contribution of managerial inefficiency in productivity regression. In addition, the results of the present paper demonstrate the importance of using confidence intervals to determine whether the results are statistically significant. For example, as indicated in Table 3, although all MFIs report technological growth but only nine of them have a significant technological progress. This information is especially useful from managerial perspective as managers can make more effort to improve the productivity of those institutions that are desperately needed improvements. We further perform a second stage regression to examine how several environmental variables influence on the productivity progress. Results suggest that younger MFIs reap the benefit of ICT to improve the productivity. Moreover, we find that higher ROA associate with the progress in productivity and innovation over the period considered.

The current investigation was limited by the observations that are available only for four consecutive years. However, this caveat is ameliorated to considerable extent by the fact that the most of the important regulatory reforms have been taken place within the sample period. Thus, the empirical results in this paper shed light on the influences of these policy reforms over the productivity growth of Kenyan microfinance market, at least in short term. Future research should therefore conduct with data for a longer period to paint a comprehensive picture on long term influences of those strategies.

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Appendix A

A survey of research in efficiency and productivity analysis of microfinance Institutions

Author	Data Source	Methodology	Input variable(s)	Output variable(s)
Nghiem et al. (2006)	44 MFIs in Vietnam	DEA	Labor and non-labor costs	Number of savers, number of borrowers and number of groups
Qayyum & Ahamad (2006)	85 MFIs in South Asia	DEA	Number of credit officers and cost per borrower	Loan disbursed by MFI
Gutiérrez-Nieto et al. (2007)	30 MFIs in Latin America	DEA	Number of credit officers and operating expenses	Number of loan outstanding, gross loan portfolio and interest and fee income
Paxton (2007)	190 semiformal financial intermediaries in Mexico	SFA	Deposits, capital and labor	Loans and investments
Bassem (2008)	35 MFIs in Mediterranean zone	DEA	Number of employees and total asset	Number of active women borrowers and return on assets (ROA)
Gutiérrez-Nieto et al. (2009)	89 MFIs from unknown number of countries	DEA	Total assets, operating costs and number of employees	Gross loan portfolio, financial revenue, number of active women borrowers and indicator of benefit to the poorest
Hermes et al. (2011)	435 MFIs from unknown number of countries	SFA	Total expenses per unit of labor, interest expenses per unit of deposits	Gross loan portfolio
Servin et al. (2012)	315 MFIs operating in 18 Latin American countries	SFA	Total assets, operating expenses and personnel	Number of loans outstanding
Piot-Lepetit & Nzongang (2013)	52 MFIs in Cameroon	Multi-DEA approach	i. Production and financial inputs Equities, assets, personnel costs, financial costs & other operating costs ii. Intermediation input Deposits	i. Production output Deposits ii. Finacial outputs Gross loan portfolio Operating revenues and other financial revenues iii. intermediation outputs

	iii. Social inputs Gross loan portfolio, operating revenues and other financial revenues	Gross loan portfolio, operating revenues and other financial revenues iv. Social outputs Number of clients, number of women borrowers and indicator of benefit to the poorest
Bassem (2014)	Number of employees and operating expenses	Interests and fee income, gross loan portfolio and loans outstanding

Governance and efficiency of microfinance institutions: empirical evidence from Sri Lanka

Abstract

Using a sample of Sri Lankan microfinance institutions (MFIs), we investigate the impacts of several governance models (i.e., board size, proportion of women on the board, a same individual serves as the Chief Executive Officer (CEO) and chairman of the board (duality) and presence/ absence of a female CEO) on MFIs' efficiency. We measure the efficiency in terms of MFIs' dual objectives of financial sustainability and outreach. The empirical investigation uses a two-stage double bootstrap procedure. In the first stage of the analysis, we design two Data Envelopment Analysis (DEA) models using same inputs and two different output measures to obtain efficiency estimates in terms of financial sustainability and poverty outreach. Then in the second stage, both efficiency dimensions are separately regressed on the governance variables. Results reveal that financial efficiency improves with a small board and higher proportion of women on the board. Results also show that MFIs in which the same individual holds CEO and chairman of the board and MFIs in which a woman holds the position of CEO are less efficient in terms of reaching the lower strata of the rural poor.

1. Introduction

Although there are a number of studies on the link between the corporate governance models as used by various firms and their performance, far too little attention has been paid to corporate governance true impact on success/ failure of microfinance programs within a financial system in general. In his seminal article, Labie (2001) for the first time analyzes several key issues related to governing structure, with special emphasis on MFIs' dual objectives of financial sustainability and outreach. He concludes that adopting of good corporate governance practices is a prerequisite to improve the MFIs' performance. In addition, there are several empirical studies to find the link between governance and performance of MFIs. Hartarska (2005) uses a small sample of MFIs in Eastern Europe and Central Asia to examine the correlation between performance and board characteristics, managerial compensation, external rating and auditing. Financial performance is measured by return on assets (ROA) and operational self-sufficiency (OSS). Outreach is measured in two dimensions: breadth and depth. Number of active borrowers and average loan balance are used as proxies for breadth of outreach and depth of outreach dimensions, respectively. She finds that performance-based compensation of managers is not associated with better-performing MFIs. Moreover, her results also indicate that managers' experience improves MFIs performance whereas a more independent board as evidenced by giving a better return on assets (ROA). Mersland & Strom (2009) examine the relationship between performance and various corporate governance mechanisms in MFIs using a self-constructed global dataset on rated MFIs. MFIs performance is measured in terms of financial sustainability and outreach. They use ROA, operational self-sufficiency (OSS), portfolio yield and operational costs as proxies for financial performance whereas average loan balance and number of clients are included as indicators of outreach performance. They find that financial performance improves with local rather than international directors, an internal board auditor, and a female CEO. They further reveal that breadth of outreach increases with duality (same individual holds Chief Executive Officer (CEO) and chairman of the board). Their results highlight the need for an industry specific approach to MFI governance. Strom et al. (2014) investigate the relations between woman leadership, institute performance, and corporate governance models of 329 MFIs in 73 countries over the period from 1998 to 2008. Empirical findings show that a female CEO and a female chairman of the board are positively related to financial performance of MFIs as measured by ROA. In contrast to studies based on traditional accounting ratio that fail to paint a coherent picture of MFIs' performance when multiple inputs and outputs are used (see Sherman & Gold, 1985; Siriopoulos & Tziogkidis, 2009), Hartarska & Mersland (2012) use the Stochastic Frontier Analysis (SFA) technique for performance benchmarking. They investigate the influence of several governance mechanisms on MFIs' financial sustainability and breadth of outreach efficiency dimensions. Their findings reveal that efficiency increases with board size of up to nine members and decrease after that. They also show that MFIs in which the CEO chairs the board and MFIs with a larger proportion of insiders on the board are less efficient. However, their study fails to reveal how MFIs efficiency in terms of reaching the lower strata of the rural poor is influenced by corporate governance mechanisms. On the other hand, from a methodological point of view, the main drawback of the SFA, the method employed by them, is that it assumes a priori specification on the production function. This limitation may lead to estimate inaccurate parametric cost function.

The purpose of the present study is to investigate the impacts of several governance characteristics (i.e. board size, proportion of women on the board, duality and presence of a female CEO) simultaneously on MFIs' dual objectives of financial sustainability and depth-of- outreach (hereafter poverty outreach). In contrast to the previous studies based on traditional accounting indicators and SFA technique, the present study extends the existing research as follows. First, we use the two-stage double bootstrap approach proposed by Simar & Wilson (2007). In the first stage, we use Data Envelopment Analysis (DEA) technique to obtain the efficiency scores of individual MFI. Efficiency is measured in two dimensions- financial and depth of outreach. Then in the second stage, efficiency scores yielded in the first stage are regressed on governance variables using the bootstrap truncated regression. The innovative double bootstrap method used in the present study enables to make valid inference about the impact of governance characteristics on MFIs' efficiency. Additionally, use of DEA that works well with small samples as compared with SFA (Wouterse, 2010) is more appropriate in the context of Sri Lankan microfinance industry as relatively a small number of MFIs operate in Sri Lanka. Second, we extend the earlier study of Hartarska & Mersland (2012) by focusing explicitly on the impacts of corporate governance characteristics simultaneously on financial and poverty outreach efficiency dimensions. The latter variable account for the depth of poverty of the clients served. Finally, in comparison to cross-country studies that may fail to fully acknowledge the differences in regulatory framework and level of competition in domestic markets (Balkanhol, 2007), firm specific characteristics and policy induced shocks (Berger & Humphrey, 1997), we consider a sample of 36 Sri Lankan MFIs for our investigation. In order to obtain homogeneous sample, we include only the companies and Non Governmental Organizations (NGOs) that are collectively called as NGO-MFIs. Moreover, focusing on a single country in the current study helps us to obtain a geographically homogeneous sample. On the other hand, the microfinance industry in Sri Lanka is of particular interest to investigate the relationship between efficiency and governance mechanisms as MFIs play a significant role in country's economy. Nevertheless, Microfinance Industry Report (2010) reveals that weak corporate governance is a main issue in Sri Lankan microfinance sector. The report maintains that "over-interference in government controlled entities can result in ill-qualified individuals with little or no sector experience being placed on the boards of MFIs, and arbitrary interference in management". Furthermore the report states that "In NGO-MFIs which originally began as social welfare organizations, strong founder members or family groups often dominate the institution and have complete decision making power. In many instances resistance from these groups proves a barrier to the introduction of transparent governance procedures." The prevailing legal vacuum is mainly attributable to these weak governance mechanisms (Asian Development Bank Completion Report, 2012). Thus, understanding of how the governance mechanisms influence on both dimensions of efficiency is essential for managers and policy makers to implement appropriate policy instruments. To the best of our knowledge, this is the first empirical study to investigate the relationship between governance mechanisms and efficiency of MFIs in Sri Lanka. Findings of this study, therefore, provide some insights to the policy makers to develop sound corporate governance system in order to improve the duel objectives of microfinance programs.

The remainder of the paper is organized as follows. Section two presents the methodology, data and variable specifications. Section three reports the results. Section four concludes.

2. Methodology and Data

2.1 Data Envelopment Analysis (DEA)

DEA has been developed by Charnes et al. (1978) using the seminal work of Farrell (1957) and others. It is a non-parametric linear programming technique used for evaluating relative efficiency of a set of homogeneous Decision Making Units (DMUs) having multiple inputs and multiple outputs. DMUs with efficiency score equals to one are fully efficient and they lie on the constructed frontier, and those are assigned the score less than one are relatively inefficient and their input and output values locate some distance away from the corresponding reference point on the production frontier. They are recognized as inefficient. There are several DEA models with different assumptions in DEA. Among them, CCR (Charnes et al., 1978) and BCC (Banker et al., 1984) are the widely used DEA models. The CCR model assumes that each DMU operate with Constant Return to Scale (CRS) and provides the measurement of overall technical efficiency. CRR model is only appropriate when all DMUs operate at an optimal scale. The BCC model, on the other hand, has an assumption of Variable Return to Scale (VRS) for the inputs and outputs. It delivers the measurement of pure technical efficiency. Both models can be formulated by applying an input orientation or output orientation perspectives. In an input-oriented approach, efficiency is measured as a proportional reduction in the input usage, with output levels held constant whereas an output-oriented approach requires proportional increase of outputs with constant levels of input (See, for details, Coelli et al., 2005).

In the present paper we employee input oriented BCC model with VRS assumption, assuming that all MFIs in the sample may not operate at their optimal scale. In the first stage of the analysis, we execute the input specification DEA model where we assume that managers of MFIs have less control over the output quantities compared to the available input resources. Input oriented VRS efficiency estimate, $\hat{\theta}_i^{VRS}$, for the ith MFI is obtained by solving the following linear programming problem.

$$\begin{aligned} & min_{\hat{\theta}_i^{VRS}\lambda_i} \hat{\theta}_i^{VRS} \\ & subject\ to \quad -y_i + Y\lambda \geq 0 \qquad (1) \\ & x_i\hat{\theta}_i^{VRS} - X\lambda \geq 0 \\ & N1'\lambda = 1 \\ & \lambda \geq 0 \end{aligned}$$

Where $y_i$is a vector of outputs, x_i is a vector of inputs, N1 is an N X 1 vector of ones. λ is an N x 1 vector of constant.

2.2 Second-stage double bootstrap truncated regression

In the second-stage of the analysis, efficiency estimates obtained in the first stage are regressed on several governance variables. Although censored models (including Tobit estimator) are widely used in the second stage analysis, Simar & Wilson (2007) highlight two main drawbacks with such conventional regression approaches. First, they point out that the efficiency scores estimated in the first stage are likely to be biased in finite samples. Second, the efficiency scores are not independent observations as the estimation of the efficiency for one DMU incorporates all other DMUs in the sample. Consequently, the error term is serially correlated and standard methods to inference are invalid. In their studies with Monte Carlo experiments, Simar & Wilson, (2007) address these issues by proposing an alternative double bootstrapped procedure that permits the consistent inference while simultaneously generating standard errors and confidence intervals for the efficiency estimates. Thus, following, Simar & Wilson (2007), the second stage regressions in the present study are estimated using the following regression specification:

$$\hat{\theta}_i = a + z_i\beta + \varepsilon_i, \quad i = 1, \dots, n \quad (2)$$

Where a is a constant term, z_i is a vector of variable that represents a governance characteristic for i^{th} MFI, β is a vector of parameters and ε_i is the statistical noise. We refer to Simar & Wilsn (2007) for technical details on the bootstrap algorithm applied in the present paper. Following Simar & Wilson (2007), the present study performs 2000 bootstrap iterations.

2.3 Data

Data are collected for 36 MFIs in Sri Lanka for 2011. The data is sourced mainly from *Microfinance Review* published by Lanka Microfinance Practitioners' Association (LMFPA, 2012) that follows the MIX Market standards[2] in reporting the data. Information about duality and presence of a female CEO are obtained from contacting the individual institutions (physical and phone contacts). In order to obtain homogeneous sample, only NGO-MFIs are considered. Licensed Specialized Banks (LSBs) and Cooperatives are excluded as they have different regulatory standards and requirements. The real names of MFIs in our observations are not disclosed in order to preserve their anonymity. Each MFI is represented by number (i.e. 1, 2, 3, …, 36).

2.4 Input and output specification

We use the production approach (Coelli et al., 2005) which views the MFIs as production units that produce services for their customers by using resources such as labors, technology, materials and the associated costs. We also observe the thumb rule that the minimum number of MFIs in the sample should be greater than three times the sum of input and output variables (Cooper et al., 2001). The variables selected for the present study are commonly used in the earlier studies on MFI efficiency.

We design two DEA models using the same inputs and two different output measures to obtain DEA estimates simultaneously along financial and outreach perspectives. The input variables selected include operating expenses and total number of employees which have often been used in earlier empirical studies on MFI efficiency (eg:, Gutiérrez-Nieto et al., 2007 and 2009; Piot-Lepetit & Nzongang, 2013). On the other hand, we use two different output variables to capture the efficiency estimates from financial and poverty outreach

[2] http://www.mixmarket.org/about/faqs/glossary

perspective. Following previous literature (e.g. Gutiérrez-Nieto et al., 2007 and 2009; Piot-Lepetit & Nzongang., 2013), financial efficiency and poverty outreach DEA models are constructed by using gross loan portfolio, and total number of woman borrowers as the measure of output variables, respectively. We select number of woman borrowers as an output variable as it indicates a better quality outreach to the poor (Kar, 2012). Selecting of women as the proxy of poverty outreach is more appropriate in the present study as women are the predominant clients of MFIs concerned. Table 1 provides the descriptive statistics of input and output variables.

2.5 Corporate governance variables and development of hypothesis

Following the earlier studies that focus on the relationship between performance and governance characteristics of MFIs, we select four corporate governance variables (i.e. board size (BSIZ), number of women on the board (WOB), Duality (DULTY) and presence of a female CEO (FECEO)) to propose the following hypotheses.

2.5.1 Board Size

Board size is measured by the number of board members. A number of studies suggest that smaller boards perform better than larger boards as the latter may lead to coordination and director free-riding problems (Jensen, 1993; Lipton, & Lorsch, 1992; Yermack, 1996). On the other hand, some other studies challenge the aforementioned notion by providing evidence that large boards positively impact on performance (Coles et al., 2008; Belkhir, 2009). Since the effect of board size on performance remains inconclusive, we propose the following hypothesis.

Hypothesis 1, H0: Board size has a significant effect on the performance of MFIs.

2.5.2 Women on the board

Women on the board as measured by the number of female board members are included as governance indicator in terms of gender diversity. Since microfinance is to a large extent a woman's business (Strom et al., 2014), having a significant number of women on the board may overcome the information asymmetry problem. This may consequently lead to a better performance of MFIs. Thus the following hypothesis is proposed.

Hypothesis 2, H0: The presence of women on the board leads to a better MFI performance.

2.5.3 Duality

Duality indicates that a same individual serves as the CEO and the chairman of the board. In the present study, duality is represented by a dummy variable. It takes the value of unity if the CEO is also chairman of the board and zero if this is not the case. Empirical studies on effect of duality on firms performance yield mixed results (Baliga et al., 1996). For example, some studies (eg: Tian & Lau, 2001; Belkhir, 2009) find that duality positively influences firm performance whereas the evidence provided by other studies (eg:, Pi & Timme, 1993; Jensen, 1993; Hartarska & Mersland, 2012) supports for the proposition that firms that have different individuals for CEO and board chairman are more effective. In the present paper, therefore, we propose hypothesis three as follows:

Hypothesis 3, H0: Duality has a significant effect on the performance of MFIs.

2.5.4 Female CEO

Effort to investigate the impact of female CEO on the performance of firms is of relatively recent vintage. Mersland & Strom (2009) make the first attempt to assess the role of a female CEO on a MFI's performance. Since women are the predominant clients of MFIs in our sample, we expect the role of a female CEO significantly influences MFI performance.

Female CEO included in the present study is a dummy variable that takes the value of unity if the CEO is a woman and zero otherwise. The proposed hypothesis is as follows:

Hypothesis 4, H0: The presence of a female CEO leads to a better MFI performance.

Table 1
Descriptive statistics of input and output variables

Variable	Unit	Mean	Std. Dev.
Inputs			
Operating Expenses'000	LKR	33,217	70,849
Total Employees	Number	79	168
Output (Financial Model)			
Gross Loan Portfolio' 000	LKR	192,616	438,457
Output (Outreach Model)			
Women Borrowers	Number	8,257	16,277

LKR: Sri Lanka Rupees; Std. dev.: standard deviation

3. Empirical Results

Table 2 reports the financial and poverty outreach efficiency estimates for 36 Sri Lankan MFIs in year 2011. The yielded efficiency score ranges between 0 and 1. MFIs with a DEA score equal to one are fully efficient and lie on the constructed frontier. On the other hand, MFIs that are assigned a score less than one are relatively inefficient and their input and output values are located a some distance away from the corresponding reference point on the production frontier.

Looking at the financial and outreach efficiency scores, we observe that a significant number of MFIs are inefficient on both efficiency dimensions. A closer look at these results reveals that most MFIs that are effective on the poverty outreach dimension are financially also efficient. This finding is consistent with Gutiérrez-Nieto et al. (2009) who argue that being financially sustainable is important for MFIs to meet their social responsibilities.

Table 3 reports the estimated coefficients and both lower bound (LB) and upper bounds (UB) for the 95 percent confidence intervals (CI) for both financial efficiency and poverty outreach efficiency estimates. At the level of governance mechanisms, BSIZ has a negative and significant impact on the financial efficiency suggesting that smaller boards are more effective on the financial efficiency dimension. This finding is consistent with Hartarska (2005) who finds that MFIs with smaller boards achieve better sustainability measured through ROA. The effect of BSIZ on the poverty outreach efficiency is, however, not statistically significant. The coefficient for WOB remains positive and significant with financial efficiency indicating that MFIs with higher proportion of women on the board tend to have higher financial efficiency. This finding is in line with the view that having a significant number of female board members in a business that mainly focuses on female clients may overcome the risk of information asymmetry, at least to a certain extent. However, the coefficient concerning the relationship between WOB and poverty outreach efficiency is not significant suggesting that WOB makes no influence on poverty outreach. DUALI shows no significant relation to the financial efficiency. However, the coefficient of DUALI is negative and statistically significant for poverty outreach efficiency suggesting that have separate CEO and chairman of the board positions perform better in terms of poverty outreach than MFIs in which the CEO chairs the board. This finding is in line with the agency theory that indicates separate titles would enhance the effectiveness of a board in carrying out its monitoring role (Lorsch and MacIver, 1989). The coefficient for FECEO indicates no influence on the financial efficiency. Nevertheless, the negative and significant coefficient for FECEO with the poverty outreach efficiency shows that MFIs in which the position of CEO is held by a woman are less efficient in terms of reaching the lower strata of the rural poor.

Table 2

Financial efficiency and poverty outreach efficiency scores for Sri Lanka MFIs

MFI	Financial Efficiency	Poverty outreach efficiency	MFI	Financial Efficiency	Poverty outreach efficiency
1	0.4891	0.3759	19	0.4786	0.2377
2	0.4647	0.4199	20	0.5843	0.4545
3	0.5669	0.5872	21	0.6777	0.9459
4	0.2448	0.2617	22	1.0000	0.4797
5	1.0000	1.0000	23	0.7332	0.4561
6	0.8021	0.7064	24	0.5551	0.4444
7	1.0000	1.0000	25	1.0000	1.0000
8	0.9341	1.0000	26	1.0000	1.0000
9	0.5114	0.7672	27	1.0000	1.0000
10	0.8539	0.6392	28	1.0000	1.0000
11	1.0000	0.6064	29	0.9564	1.0000
12	0.2872	0.2311	30	0.6067	1.0000
13	0.8000	0.8000	31	1.0000	1.0000
14	0.5714	0.5714	32	0.8000	0.8000
15	0.9301	1.0000	33	0.2883	0.4184
16	0.5025	0.4412	34	0.7756	0.5179
17	0.9566	0.5634	35	0.8289	0.3689
18	1.0000	0.5049	36	0.8993	1.0000

Table 3
Truncated bootstrapped regression results (Total number of iterations = 2000)

Variable	Financial efficiency			Poverty outreach efficiency		
		95% CI			95% CI	
	Coefficient	LB	UB	Coefficient	LB	UB
Constant	2.1236	1.4063	2.8409	2.2675	1.4499	3.0851
BSIZ	-0.0951*	-0.1808	-0.0093	-0.0210	-0.2275	0.1854
WOB	0.1639*	0.0422	0.2856	0.1336	-0.0633	0.3305
DULTY	-0.3755	-0.8813	0.1304	-0.7270*	-1.2790	-0.1750
FECEO	-0.7369	-1.5226	0.0488	-1.1164*	-1.9526	-0.2801

(*): Significant at the 1% level

LB: Lower Bound; UB: Upper Bound; CI: Confidence Interval

4. Conclusion

Although corporate governance practices play a critical role in improving MFIs performance (Labie, 2001), little is known on how they impact on the dual objectives of serving the poor in a financial sustainable way. Thus, the main objective of the present study is to uncover the impact of several governance characteristics simultaneously on financial and poverty outreach efficiency estimates using a sample of 36 Sri Lankan MFIs. Moreover, from the methodological perspectives, the novelty of the current paper lies on the use of double bootstrap approach proposed by Simar & Wilson (2007) that permits the consistent inference while simultaneously generating standard errors and confidence intervals for the efficiency estimates. Thus, the policy conclusions derived are more meaningful.

Our results suggest that a considerable number of Sri Lankan MFIs are inefficient on both financial and poverty outreach dimensions of efficiency. Moreover, second-stage results reveal that, in the case of Sri Lankan MFIs, smaller boards and the presence of a higher proportion of woman on the board tend to be more efficient in financial term. We also find evidence that duality and the presence of a female CEO have a significantly negative impact on poverty outreach. Overall, the findings of the present paper emphases the importance of implementing a sound corporate governance policy system to improve the performance of MFIs. While the generality of the results is limited given that the present study focuses on Sri Lankan MFIs, the policy implications derived can be applicable to MFIs operate elsewhere with similar socio-economic characteristics.

The main limitation of the present study is that our analysis is based on the cross-sectional data for one year. Thus, future investigations using data for multiple years and more corporate governance variables would be an important extension to the present paper.

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