Performance of microfinance institutions in achieving the poverty outreach and financial sustainability: When age and size matter?

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Performance of microfinance institutions in achieving the poverty outreach and financial sustainability: When age and size matter?

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Abstract

Using a two-stage DEA bootstrapped metafrontier approach, we investigate the effects of age and size on efficiency estimates of microfinance institutions (MFIs). In the first-stage, we use a metafrontier model combining with DEA bootstrapped procedure to obtain statistically robust and comparable efficiencies. In the second-stage, we employ a bootstrapped truncated regression to account for the impact of exogenous factors on both dimensions of efficiency. Results highlight the importance of model specification for MFIs operating in different geographical regions. Moreover, we find that although older MFIs perform better than younger ones in terms of achieving financial results, they are relatively inefficient in achieving outreach objectives. We also document that MFI size matters: larger MFIs tend to have higher financial and outreach efficiency.

Keywords- Data envelopment analysis; Metafrontier; Bootstrap; Efficiency; Microfinance

JEL Classification: G21; O16

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1. Introduction

In emerging markets, Microfinance Institutions (MFIs) are often considered to play an increasingly critical role in the development of economic system. They serve the poor who have been excluded from formal financial institutions, providing a wide range of financial services and products ranging from simple credit facilities to savings, remittance, insurance and many others. Despite several sustainable rural financial intermediations that have simultaneously achieved dual objectives of financial sustainability and social outreach, a large number of MFIs across the developing world still fail to address the widely demanded financial services in rural markets in a cost effective way (Yaron, 1994; Hermes & Lensink, 2011; D'Espallier et al. 2013). Since the successful MFIs appear to be larger and some of them grow faster than the less successful MFIs, there is an emerging consensus among donors and policy makers that performance of MFIs is influenced by age and size (Balkenhol, 2007). In this context, determination of whether older MFIs perform well on the dual objectives of financial sustainability and outreach than younger ones and whether larger MFIs are more effective on both financial and social dimensions than smaller ones could shed light on important policy implications.

Among the various possible ingredients, Gonzalez (2007) highlights age and size as major drivers of inefficiency in microfinance provisions. Although there are several studies investigating the MFIs efficiency and its determinants, there is as yet little information on the potential impact of age and size on MFI efficiency, notably in terms of the double-bottom line objective of serving the poor in a financially sustainable way. More recent evidence, though anecdotal, show that older MFIs are superior in performance to younger (Paxton, 2007) whereas the other findings reveal that younger MFIs perform better than older (Hermes et al., 2011). Theoretical and empirical studies to investigate the impact of size on MFIs performance are scarce, with the exception of Hartarska & Nadolnyak (2007) and Cull et al. (2011). Although the relationships have been inconclusive and ambiguous in earlier empirical studies, it would be very important to explore in this research how age and size influence on MFIs' financial and outreach efficiency measures. To the best of our knowledge, no research exists that focuses explicitly on the effects of age and size simultaneously on both financial and outreach efficiency dimensions of MFIs.

The purpose of the present study is to empirically investigate the impact of age and size on the performance of MFIs, measured by dual objectives of financial sustainability and outreach. While the term financial sustainability refers to ability of an MFI to achieve unsubsidized, full cost recovery, outreach is taken to mean extending financial services to a large number of people (breadth of outreach) and towards the lower income strata of the rural poor (depth of outreach). See Yaron et al., 1997; Conning, 1999; Schreiner, 2002 for more details about different outreach aspects. Though several methods are often used, there is no universal agreement on the specification of evaluating and measuring financial institutions performance (Paradi & Zhu, 2013). The commonly used methods in MFIs performance appraisals include traditional financial ratios (e.g., Hartarska, 2005; Strom et al, 2014), performance evaluation framework articulated by Yaron (1992a) (e.g., Paxton, 2003; Hudon & Traca, 2011; Nawaz, 2010; Aveh et al., 2013; Sharma, 2014) and production frontier based techniques (e.g., Gutiérrez-Nieto et al., 2007; Paxton, 2007; Gutiérrez-Nieto et al., 2009; Hermes et al., 2011; Servin et al., 2012; Piot-Lepetit & Nzongang, 2014; Wijesiri et al., 2015; Wijesiri & Meoli, 2015). While effective in some circumstances, use of ratio measures to evaluate the performance of financial institutions has not escaped serious criticism from academics. Athanassopoulos & Ballantine (1995), for example, argue that traditional financial ratios are not suitable for considering the effects of economies of scale and estimation of overall performance measures due to their univariate nature. Especially, MFIs are concerned, as some financial ratios designed for evaluating MFIs financial performance, like financial self-sufficiency (FSS) fail to capture subsidies associated with MFIs' operations, including among others, the full opportunity cost of MFI's equity that is considered a free cost item in accounting terms and the full value of subsidies embedded in the MFI's concessionary borrowing (Yaron 1992a; Francisco et al., 2008; Manos & Yaron, 2009a). Yaron (1992a) addresses these issues that are inherent in traditional ratios, in the context of microfinance industry, by proposing an alternative performance evaluation framework that uses self–sustainability and outreach of MFIs as two primary assessments criteria, measured by subsidy dependent index (SDI) and outreach index (OI), respectively. Subsidy granted to MFI and measured by the SDI is an input of social cost of subsidized MFIs and one of the most heavily weighted factors upon which further access to donor capital is conditioned (Conning, 1999), while the outreach is the social output. OI is different from econometric measurement of MFI's impact of operations (e.g., Randomized control tests). It is a hybrid, arbitrary, flexible index that measures the achievement of MFIs with respect to its predetermined social objectives, thereby, reflecting level of achievements along priorities set by policy makers and funds and subsidies' providers namely, donors and states. Moreover, OI unlike econometric measurement doesn't claim to capture the full impact of the MFI's operations on clients welfare but it is friendly user and inexpensive to apply. In contrast econometric measurements are, much more expensive to carry out, require high skills and therefore only rarely done. In general, SDI and OI framework provide a fuller picture of MFIs overall performance in terms of the dual objectives as it escapes from the possible contaminants in MFIs benchmarking such as influence of relief from reserve requirements, access to concessionary borrowing grants, subsidies in form of free technical aid received by MFIs (Yaron & Manos, 2007; Hudon & Traca, 2011). Thus, this framework provides very useful insight for policy makers and donors in pursuit of improved resource allocation and optimizing subsidies use (Conning, 1999). Nevertheless, SDI was basically designed only to inform on the cost and subsidy involved and not on the full benefits to society caused by the MFI's operation. For example, an MFI can be socially desirable to donors in allocative terms and technically efficient under market constraints, although still subsidy dependent. This could be the result of reaching deep poverty clients whose services are associated with very high cost or by insisting on applying very low lending interest rates following a belief that this is an important 'social' tool. In other words, subsidy independence does not necessarily links with high efficiency level, nor does it necessarily label an MFI as inefficient. Production frontier based techniques such as parametric methods like stochastic frontier analysis (SFA) and non-parametric methods like data envelopment analysis (DEA) are another widely used approaches in performance benchmarking of MFIs. Comparing with other performance measuring metrics such as ratios analysis and SDI, the main advantage of frontier method is that it offers overall objectively determined numerical efficiency scores with the economic optimization mechanisms in complex service operational environments (Berger & Humphrey, 1997). Both DEA and SFA techniques have inbuilt strengths and weaknesses. See Berger & Humphrey (1997) and Berger & Mester (1997) for a detailed discussion and comparison of both methods in financial context.

In the present paper, we use a two-stage DEA approach for a sample of 420 MFIs operating across the world for simultaneously benchmarking the efficiency of MFIs along financial and outreach dimensions. Given the sample of MFIs operating in different geographical regions that are characterized by different social and economic norms, one of the important considerations in this study is whether estimating a single frontier for our evaluation provides meaningful efficiency scores. O'Donnell et al. (2008) point out that use of a common production frontier to compare the efficiency of DUMs operating under different environmental characteristics leads to yield inaccurate efficiency estimates. Since the MFIs in our sample are from different geographical regions, they could have country specific characteristics in terms of demographic, cultural and level of economic and technological advances. For example, in their empirical analysis of MFI efficiency, Gutierrez-Niéto et al. (2009) find significant differences between four different geographical regions including Asia, Latin America, Africa and Eastern Europe. Thus, estimating a common frontier for the whole sample is likely to distort the efficiency estimates yielded in the first-stage and subsequently the results of second-stage analysis (Dietsch & Lozano-Vivas, 2000). In an attempt to overcome this limitation in conventional production frontier models, Battese et al. (2004) propose a metafrontier method based on the notion of metaproduction function defined by Hayami & Ruttan (1971). Battese et al. (2004) describes metafrontier model as a deterministic parametric function and its values are no smaller than the components of the production functions of the different groups involved. This approach enables the calculation of comparable efficiencies for Decision Making Units (DMUs) operating under different technologies while acknowledging any heterogeneity between them. Yet, they only use parametric SFA in estimating the metafrontier. O'Donnell et al. (2008) further elaborate the metafrontier model to use in estimation of DEA efficiencies too. The present study employs the metafrontier model proposed by O'Donnell et al. (2008) in the analysis of the data on MFIs located in Asia, Latin America, Africa and Eastern Europe. We use nonparametric DEA method to construct the metafrontier model as it has several advantages over parametric SFA technique. The main advantage of DEA is that it removes the requirement of making arbitrary assumption regarding the functional form of the frontier. Instead of requiring a priori assumption about the analytical form of the production function, DEA construct the best practice production function on the basis of observed data. Since DEA requires no parametric assumption, it offers more-flexible forms of the technology and distribution of inefficiency than does estimation of the translog cost function (Wheelock & Wilson, 2000). Moreover, it allows choosing input and output variables according to performance assessment objectives. However, traditional DEA carries with it well known limitations. The main caveat is that the frontier is sensitive to outliers

and measurement errors since its inability to allow for random noise in efficiency measurement and assumption of all deviations from the frontier indicate inefficiency, which may lead to distort the resulted efficiency measures. We tackle this issue using the bootstrap method proposed by Simar & Wilson (1998, 2000) that allows for random error by producing statistical inferences without distorting any advantage of the DEA technique. It is also worthwhile to note that dividing the whole sample into several groups based on the MFI operating geographical regions leads to reduce the number of MFIs in each group. However, use of bootstrap method is a remedy to the issues raised by small sample size (Halkos & Tzeremes, 2012; Song et al., 2013). Then, in the second stage, bias corrected-efficiency scores are regressed on age, size and several other control variables using the double bootstrap procedure proposed by Simar & Wilson (2007) that has gained wide recognition for its ability in producing statistically robust estimates.
Results highlight the importance of model specification for MFIs operating in different geographical regions. We also find evidence in supporting the presence of learning by doing in terms of achieving financial goals. On the contrary, we find that older MFIs are relatively inefficient in achieving their outreach objectives. Moreover, we find MFI size matters: larger MFIs tend to have higher financial and outreach efficiency, attributing to presence of higher scale economies. Additionally, we wish to claim that both Subsidy SDI and DEA methods complement each other as efficiency is measured usually in comparison to peers while SDI measures social cost and subsidies in operating supported microfinance institutions. The latter facilitates computing and comparing derived specific financial ratios that are essential for evaluation the justification of support given to MFIs such as annual subsidy per borrower, annual subsidy per $ outstanding of loan portfolio of MFI and the ratio between the annual subsidy given to the MFI and the interest and fees paid by the borrowers to the MFI. Moreover, we argue that an MFI might be very effective when compared to its peers but yet highly dependent on subsidies and therefore not necessarily worth being supported within a comprehensive cost-benefit analysis. Thus, we wish to propose that both criteria might be used when deciding whether supporting this MFI is warranted or not particularly when other instruments are also considered candidates for helping the same target clientele.

Our main contribution is to extend the literature on MFIs efficiency by focusing explicitly on the impacts of age and size simultaneously along financial and outreach efficiency dimensions. As an empirical contribution, we use a bootstrap metafrontier DEA methodology that helps us to make valid inference about the impact of age and size on efficiency estimates while acknowledging the heterogeneity in MFIs operating in different geographical regions. Use of a bootstrap metafrontier method to derive statistically significant efficiency estimates and distinguish the patterns of efficiency estimates in different geographical regions could have important policy implications for policy makers, states, donors, academics, incumbents of MFIs and NGOs thinking of setting up MFIs. Especially, estimating the gap between regional frontiers and the metafrontier could help decision makers to design realistic programs for improving the performance of the relatively inefficient regions over time (see O'Donnell et al., 2008).

The rest of the paper is structured as follows. In the next section we provide the details of the empirical methodology. This is followed by the data specification of input and output variables employed. Next, the empirical results are explored. Finally, we discuss the main findings, and note the research implications of our study.

2. Methodology

In the present study, we use a two-step DEA procedure to shed light on the impacts of age and size simultaneously along financial and depth of outreach efficiency dimensions. In the first-stage, integrating a bootstrapped DEA with metafrontier model, we estimate the efficiency of each MFI from both financial and outreach perspectives. In the second stage, both dimensions of efficiency estimates are separately regressed on age and size. Both steps are briefly discussed below.

2.1 Data Envelopment Analysis

DEA is developed by Charnes et al. (1978) based on the work of Farrell (1957) and others. It is a non-parametric linear programming technique used for evaluating relative efficiency of peer DMUs that have same multiple inputs and outputs. Unlike the parametric methods, non-parametric DEA efficient frontier is not determined by some specific functional form. Instead it involves constructing a production frontier based on the actual input–output observations in the sample. Thus, DEA efficiency score for a specific DMU is measure with respect to the empirically constructed efficient frontier defined by the best performing DMUs (Paradi et al. 2011). 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. 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 frequently used DEA models. The main difference between CCR and BCC models is based on the treatment of return to scale for the inputs and outputs. The CCR model assumes that each DMU operate with Constant Return to Scale (CRS). It is probably the most widely used DEA model (Barros, 2008) and provides the overall technical efficiency of each DMU, aggregating pure technical efficiency and scale efficiency into single value (Gollani & Roll, 1989). The BCC model, on the other hand, assumes Variable Return to Scale (VRS) between inputs and outputs and delivers the measurement of pure technical efficiency. Both CCR and BCC 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). Note, however, that the CCR model provides identical results irrespective of its orientation and that is not the case with the BCC model that yields different results with the input and output formulations (Golany & Roll, 1989).

2.1.1 Metafrontier model

It is well-known that sample homogeneity is one of the fundamental assumptions of production frontier methods. This assumption on efficiency makes it impossible comparing the efficiency of DMUs operating under different production technologies (O'Donnell et al., 2008). Battese et al. (2004) take steps to remedy this issue in the SFA framework. The metafrontier model developed by them enables the measurement of comparable technical efficiencies for non-homogeneous DMUs. O'Donnell et al. (2008) further elaborate the model to use in non-parametric DEA platform too. The metafrontier model is a function that 'envelops' the individual group frontiers, each having their specific technology and environmental factors (Battese et al., 2004). Thus, this approach provides consistent and homogeneous efficiency comparison (Assaf et al., 2010). The efficiencies measured with respect to the metafrontier can be decomposed into the components of technical efficiency measured by the distance from an input–output point to the group frontier and the metatechnology ratio (MTR) that measures how close the group-frontier is to the metafrontier (O'Donnell et al., 2008). Thus, MTR for the DMUs in group k (TGR_k) can be defined as follows:

$$MTR_k = \frac{\theta^*}{\theta^k} \qquad (1)$$

Where θ^* denotes the technical efficiency with respect to the metafrontier and θ^k refers to the technical efficiency with respect to the group frontier. θ^* is always less than the θ^k and calculated MTR ranges between 0 and 1 (Mitropoulos et al., 2015). For technical details about metafrontier model in DEA framework, refer to O'Donnell et al., 2008.

2.1.2 DEA bootstrap approach

Although DEA has several undeniable advantages compared to the other frontier techniques, it suffers from several limitations. As mentioned earlier, one major drawback of the conventional DEA estimator is that efficiency is measured relative to an estimate of the true production frontier, and consequently corresponding DEA estimates are biased by construction and are sensitive to the sampling variations of the obtained frontier (Simar & Wilson, 1998). Thus, conventional DEA applications offer only point estimates without a sense of the sampling variation associated with them. The method introduced by Simar & Wilson (1998, 2000) based on the bootstrap concept (Efron, 1979) remove this inbuilt drawbacks in the conventional DEA method. The bootstrap procedure proposed by them provides confidence intervals and corrections for the bias inherent in conventional DEA without distorting any advantage of the DEA technique. The confidence intervals on the efficiencies attempt to capture the true efficient frontier within the specific interval (Dyson & Shale, 2010).

In the present study, we use the bootstrapped DEA to construct the metafrontier model. First, we estimate the metafrontier for the whole sample. Then, following Gutierrez-Niéto et al. (2009), we group MFIs in our sample into four different groups (i.e., Asia, Latin America, Africa and Eastern Europe), and construct group frontiers by using DEA for each group. We also calculate the MTR of each region by applying the equation (1). When estimating both dimensions of efficiency scores under metafrontier and groupfrontiers, we use the bootstrap DEA approach proposed by Simar & Wilson (2000) to investigate the sensitivity of efficiency estimates and MFI rankings to variations in sample composition. We execute input oriented DEA approach where we assume that managers of MFIs have less control over the output quantities compared to the available input resources. The next important issue with DEA is referred to return to scale (RTS). Seiford & Zhu (1999b) argue that the sensitivity issue of RTS can be related to changes in efficient frontier and changes of position of the efficient DMUs along the frontier. Use of inappropriate returns to scale, therefore, results in statistically inconsistent estimates of efficiency (Simar & Wilson, 2002). Thus, in the present paper, we follow the statistical hypothesis testing procedure developed by Simar & Wilson (2002) to determine whether the frontier globally exhibit constant or variable returns to scale. We define the null hypothesis (H_0) as the technology is CSR and its alternative (H_1) as the VRS as follows:

$$H_0\text{: technology is globally CRS} \qquad H_1\text{: technology is VRS}$$

Considering a given set of observations of N MFIs, we calculate the test statistic (S) using the mean of ratios of the efficiency scores (θ) as in (2).

$$S = \frac{\sum_{n=1}^{N} \theta_{CRS}^{n}}{\sum_{n=1}^{N} \theta_{VRS}^{n}} \qquad (2)$$

We, then, formulate a critical value ($c_\propto$) for S to determine whether we reject H_0 or not. If the estimated test statistic (S) value is less than the critical value and $\text{probability } (S < c_\propto | H_0) = \text{Size of the test } (\propto)$, we reject the null hypothesis and accept the alternative hypothesis of VRS. In such a situation, another hypothesis testing procedure is needed to be performed to determine whether the underlying technology exhibits increasing or decreasing returns to scale.

2.2 Second-stage regressions

In the second stage, using a regression method, we examine the effect of age and size on estimated bias-corrected efficiency estimates. The most commonly employed method in this context is the Tobit estimator. However, use of Tobit estimator to estimate the model (3) in a second stage analysis has been criticized by Simar & Wilson (2007). They argue that because of explanatory variables (z) are correlated with the disturbance term (ε), the regression assumption of ε is independent of z becomes invalid. Moreover, they point out that DEA efficiency estimates are correlated with each other, and consequently yield inconsistent and biased estimates in the second stage.

$$\theta_i = a + z_i\beta + \varepsilon_i \qquad (3)$$

Where the subscript i = 1,…, N indicates the observations, θ is efficiency score, a is a constant term and β is a vector of parameters.

In their studies with Monte Carlo experiments, Simar & Wilson, (2007) address these issues by proposing an alternative double bootstrapped procedure that permits the valid inference and takes into account the bias due to the serial correlation of the efficiency estimates.

3. Data and variables

3.1 Data

In the present paper, we use more recent database, from Microfinance Information Exchange (MIX) for year 2013 (www.mixmarket.org). MIX is a global web-based microfinance platform that provides high quality standardized information about a large number of MFIs operating in different geographical regions (Servin et al. 2012). The financial and social information available in MIX have used in several earlier studies (e.g. Gutierrez-Niéto et al., 2009; Nawaz, 2010; Ahlin et al., 2011; Hermes et al., 2011; Servin et al., 2012; Louis et al., 2013). About 30 MFIs are excluded from the study because information on their required variables was lacking. Finally, in all, we have 420 MFIs operating in different countries in Asia, Africa, South America and East European region. Our sample contains 154 Non Governmental Organizations (NGOs), 49 Credit Unions/ Cooperatives, 178 Non-Banking Financial Institutions (NBFIs) and 39 Banks. The breakdown by geographical regions is as follows: 212 from Latin America, 136 from Asia, 44 from Africa and 28 from Eastern Europe. These ownership types and geographical regions are those defined by MIX for its purpose of dissemination of data. We do not provide the dataset here as it covers 420 MFIs. Table 1 provides the number of observations per age and operating region as well as size and operating region. According to the length of their survival (in years), we divide MFIs into three categories: new (1 to 4 years), young (5 to 8 years) and matured (> 8 years). In this classification, we follow MIXMarket benchmarking procedure[4]. On the other

[4] http://www.themix.org/, accessed in January, 2015

hand, in classifying the MFIs as small, medium and large, we follow *Microfinance Tier Definitions* (www.microrate.com) and define small MFIs as those having less than US$ 5 million total assets, medium MFIs as those having US$ 5-50 million total assets and large MFIs as those having more than US$ 50 million total assets. Overall, the sample is dominated by matured and medium size MFIs and many of which is located in Latin American region.

INSERT TABLE 1 HERE

3.2 Input and output variables

There continues to be some debate about explicit definition of inputs and outputs of a financial institution. The choice of inputs and outputs needs to be consistent with the DEA approach to be employed and activities carried out by firms (Gregoriou et al. 2005). There are three well-recognized approaches commonly used in the literature: production, intermediation and profitability models (Paradi et al. 2011). Under the production approach, the financial institutions are defined as production units that produce services for their customers by using resources such as capital and labor. The intermediation approach views the financial institutions as intermediaries that employ labor, deposits and physical capital to produce loans and 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. The profitability approach, on the other hand, is used to measure the profitability of DMUs that use inputs (expenses) to produce its outputs (incomes). There is no straightforward agreement among researchers on what input and outputs should be considered in the analysis (Berger & Humphrey, 1997). In general, the selection of appropriate model is based on data availability (Paradi et al., 2011). Since most MFIs across the world are not deposit-taking institutions (Galema et al., 2011), the role of deposit becomes an irrelevant factor in this study.

In the present study, we construct two DEA models using same inputs and different output measures to estimate the efficiency of MFIs from both financial and social perspectives. Given data availability and consistent with Gutiérrez-Nieto et al. (2007), we select two inputs (i.e., operating expenses and total number of employees). Also, following previous empirical literature on MFI efficiency, we choose four outputs variables (i.e., gross loan portfolio, financial revenue, inverse of average loan balance per borrower and number of active borrowers). These output variables capture the MFI dual objectives of financial sustainability and poverty outreach. Additionally, following Cooper et al. (2001), we observe a thumb rule to make sure that the minimum number of DMUs is at least three times greater than the sum of input and output variables [420 > 3 (2 + 2)]. Observing of this heuristic in DEA studies is essential to avoid model saturation effects (Edirisinghe & Zhang, 2010). Operating expenses and total number of employees which have commonly been used in prior studies to investigate the efficiency of banks (e.g., Berger & Humphrey, 1997; Berger & Mester, 1997; Athanassopoulos, 1997) and MFIs (e.g., Gutiérrez-Nieto et al., 2007 & 2009; Wijesiri et al., 2015; Wijesiri & Meoli, 2015) are selected as the input variable measures. On the other hand, with regard to choice of output variables, selection is quite challengeable due to the heterogeneity in types of services and products provided by MFIs. In general, output variables reflect a mix of quantitative and qualitative measures of results expected (Golany & Storbeck, 1999). Thus, in order to find more appropriate output variables, we consider the dual objectives pursued by MFIs. In line of earlier literature on MFI efficiency (Gutiérrez-Nieto et al., 2007 & 2009; Piot-Lepetit & Nzongang, 2014; Wijesiri et al., 2015) and banks (Athanassopoulos, 1997; Seiford & Zhu, 1999a; Tzerermes, 2015), we take gross loan portfolio and financial revenue as output measures to construct the financial model. With regard to the outreach efficiency model, following Widiarto & Emrouznejad, (2015), we include inverse of average loan balance per borrower and number of active borrowers as output measures. Average loan balance per borrower, often taken to be a proxy for the poverty level of customers (Cull et al., 2007), is measured by the average loan size per borrower divided by the gross national income (GNI) per capita. Number of active borrowers, on the other hand, is a proxy for breadth of poverty outreach. All else constant, the number of borrowers served by an MFIs depends on the level of subsidies that it can attract (Schreiner, 2002).

With respect to the social model, we acknowledge some potential with the indicator of benefit to the poorest (PI) that is often used as social output measures in earlier studies (e.g., Gutiérrez-Nieto et al., 2009 ; Piot-Lepetit & Nzongang, 2014), albeit we do not welcome it as an appropriate output variables to construct the social model in our analysis. We use the following simple example to illustrate one of the major problems associated with PI in DEA application. Consider two MFIs, X and Y in a sample of 35 MFIs, whose standardized average loan balance per borrower (K), number of active borrowers and number of women borrowers are shown in Table 2.

INSERT TABLE 2 HERE

Then estimation of PI for both X and Y is obtained as (Gutiérrez-Nieto et al., 2009):

$$\mathrm{PI} = \left(1 - \frac{K_i - \mathrm{Min}(K)}{\mathrm{Range}\ (K)}\right) \text{ X Number of active borrowers} \qquad (4)$$

where K is measured by average loan balance per borrower over GNI per capita, Min (K) is the minimum value of K over all MFIs and range of (K) is the difference between maximum value of K and the minimum value of K over all MFIs.

Suppose Min (K) and Range of (K) for MFIs in this sample are 2 and 18, respectively. Using the formula (4), the estimated PI for X and Y is 0 and 138, respectively. Since, MFIs with higher PI values have more poverty outreach (Gutiérrez-Nieto et al., 2009), Y is more effective in achieving the poverty objectives compared to X. However, as can be seen from the Table 2, X claims for a larger number of active borrowers and all of whom are females (a proxy for depth of outreach). This indicates the higher scale of outreach accomplished by X compared to its counterpart Y. Thus, it is reasonable to argue that the conclusion made based on PI that Y is more poverty oriented compared to X is not meaningful. On the other hand, the main consideration guided us in choosing the number of active borrowers instead of number of women borrowers is that MFIs operate in some geographical regions (for example countries dominated by Islamic law) tend to focus on family borrowers (Widiarto & Emrouznejad, 2015). In other words, despite the facts that loans to women have higher marginal impact than to men (Pitt & Khandker, 1998), MFIs operating in some geographical areas do not lend directly to women. For example, lending to women may be considered as a social goal in Bangladesh where women have hardly access to borrowing but this is utterly a non issue in West Africa where women play a major role in trade and businesses. Even in Bangladesh and similar countries that MFIs take affirmative action and lend only or primarily to women, the issue is who decides what will be done with the money-is it formal borrower, the women or the husband. Since our sample consists of MFIs from all over the world, use of number of women borrowers as an output variable in the social model may result in biased efficiency estimates. Thus, we use number of active borrowers as an output variable.

Table 3 presents the variables used in the DEA analysis along with descriptive statistics, the mean and standard deviation. Overall, the mean values of all variables are larger than the respective standard deviations (Std. dev.). Thus, MFIs in our sample differ substantially with respect to their input usage and output production. Table 4 illustrates definitions of input and output variables used in the analyses. All financial variables are measured in United States Dollars (US$).

INSERT TABLE 3 HERE

INSERT TABLE 4 HERE

3.3 Environmental Variables

3.3.1 MFI Age

Age of an MFI is measured in years since its inception. It can be taken as an indicator of the experience and managerial ability of microfinance programs. The effect of age on technical efficiency can be twofold. Some researchers (Ledgerwood, 1998; Paxton, 2007) argue that efficiency improves as an MFI get mature. This can be due to several factors: it could be the result of higher operating costs experienced by MFIs that first get off the market (Paxton, 2007). Until they establish in the market by implementing suitable business models ("learning by doing"), they may have to bear higher operating costs. It could also be due to the ability of older firms to cushion the short term losses compared with younger firms (Grable & Lytton, 1998). On the other hand, others (e.g., Hermes et al., 2011) provide evidence that age is negatively associated with technical efficiency. This may be due to the fact that as firms age, they become less able to respond to the new challenges (Barron et al. 1994).

3.3.2 MFIs Size

Literature on efficiency of banks and MFIs provide evidence that size is an important source of bank efficiency. Size reflects the capacity of firms to compete with others in the market (Gonzalez, 2007; Staub et al. 2010) as well as firm's market's awareness (Nhung & Okuda, 2015). Moreover, institutional size helps to account for the effects of differences in technology, diversification, investment opportunities and other factors related to size (Berger & di Patti, 2006). Thus, we included size as an exogenous variable to see if the MFI's size is related to its degree of both dimension of efficiency estimates. Given the data availability, we measure the size of MFIs in terms of their total assets.

Additionally, several variables that are likely to influence efficiency estimates are included to control for the strategic niche of MFIs. These variables include: type of ownership (TYPE), return on assets (ROA), debt to equity ratio (DEQR) and the geographical regions of MFIs operate (REGION). Including of these variables further improves the comparability of efficiency estimates. MFI ownership type is measured with TYPE dummy variable and it accounts for effect of governance and regulatory models on financial and outreach efficiency estimates. Following Servin et al. (2012), we include four types of ownerships: Credit Unions (CU), Non-Bank Financial Intermediaries (NBFI), Banks (BANK) and Non-Governmental Organizations (NGO). We assume that financial and outreach efficiencies of MFIs depend on their ownership types as MFIs belong to different ownership structures seek different trade-offs of financial sustainability and poverty outreach. In other words, the relative weights of financial and outreach objectives differ by type of ownership (Servin et al. 2012). As a proxy for profitability, we include the ROA, calculated as MFI profit after tax divided by total assets. It measures how effectively assets of MFIs are being used to generate profits. Moreover, we include DER as a proxy for MFIs leverage intensity that could be more of a tendency of donors to support more the 'social' 'MFIs with lending, particularly concessionary lending.

In order to determine the relationship between MFIs efficiency and age and size, following regression model for both financial and outreach efficiency measures is separately estimated.

$$\theta_i = \beta_0 + \beta_1 AGE_i + \beta_2 SIZ_i + \beta_3 TYPE_i + \beta_4 ROA_i + \beta_5 DER_i + \beta_6 REGION_i + \varepsilon_i \quad (5)$$

Where θ_i is the bias-corrected efficiency of the i^{th} MFI yielded in the first stage, AGE indicates the operation years of an MFI since inception. It is a dummy variable (equals one if a MFI is new, equals zero otherwise; equals one if a MFI is young, equals zero otherwise), SIZE is the size of an MFI. It measures in terms of total assets that include total of all net assets. TYPE is a dummy variable (equals one if a MFI is CU, equals zero otherwise; equals one if a MFI is NBFI, equals zero otherwise; equals one if a MFI is bank, equals zero otherwise), ROA is the net profit before tax divided by total assets, DER is a proxy for MFIs leverage intensity and measured by total liabilities divided by total equity, REGION is a dummy variable (equals one if a MFI has been in operation in Asia, equals zero otherwise; equals one if a MFI has been in operation in Latin America, equals zero otherwise; equals one if a MFI has been in operation in Africa, equals zero otherwise), and ε is statistical noise.

The bootstrap estimates are produced using 2000 bootstrap replications. We use FEAR package (Wilson, 2008) in the platform of R software to estimate the DEA efficiency estimates and second stage truncated regression results. For the sake of brevity, we do not present the bootstrap algorithms employed in the present paper. Interested readers are encouraged to consult Simar & Wilson (1998, 2000, and 2007) for technical details.

4. Results

4.1 Return to scale test

A statistical hypothesis testing procedure as proposed by Simar & Wilson (2002) is undertaken to determine the type of return to scale technology defined by the best performers in the sample. Table 5 presents the estimation result of equation 2. Since tests statistic (S) values for both models are greater than the respective critical values (α), we do not reject the null hypothesis. Thus in the present study we employ the CCR model assuming that each MFI in our sample operate with global CRS technology. The choice of CCR model to measure efficiency in this study can also be justified based on the fact that CCR scores have traditional more variation and its ability to identify the overall efficiency compared with BCC scores (Golany & Roll, 1989; Barros & Dieke, 2008).

INSERT TABLE 5 HERE

4.2 First-stage results

Table 6 provides the summary of bootstrapped metafrontier results for MFIs in each geographical region. The first 3 panels of the table depict the mean and standard deviations (std. dev.) of group technology original efficiency (GTOE), group technology bias-corrected efficiency (GTBCE) and the lower bound (LB) and upper bound (UB) of the 95% confidence interval for group frontiers (GTCI). Then next 3 panels provide the mean and standard deviations of metatechnology original efficiency (MTOE), metatechnology bias-corrected efficiency (MTBCE) and LB and UB of the 95% confidence interval for metafrontier (MTCI). The last panel of the table shows the MTR for MFIs in each region. MTR is measured by the gap between groupfrontier and metafrontier as indicated in equation (1). Note that calculation of MTR using bias-corrected efficiency scores lead to generate values greater than 1 for some regional frontiers. Thus, following Fallah-Fini et al. (2012), we use original efficiency scores for calculating MTR that falls between 0 and 1.

As can be seen from the table, mean GTOE and MTOE values for financial efficiency (FE) and outreach efficiency (OE) remain outside the respective confidence intervals (CI) whereas mean GTBCE and MTBCE values for both dimensions of efficiency remain inside the respective confidence intervals of lower bound (LB) and upper bound (UB). 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. Thus, it is clear that relying on original efficiency estimates could lead to misleading policy conclusions.

Looking now at the mean values of GTBCE, we observe that mean FE scores range between 0.22 (Asia) and 0.62 (Africa).This indicates a high degree of heterogeneity in FE scores for MFIs in 4 different geographical regions in the estimated group frontiers. Mean OE values range between 0.28 (Africa) and 0.43 (Eastern Europe), indicating the same trend as above. It is also notable that the standard deviation of OE is considerably higher than that of FE scores. The smaller standard deviations for FE indicate a high degree of financial efficiency homogeneity in each region whereas the considerably higher standard deviations for OE indicate higher heterogeneity of outreach efficiency within each region, with the exception of Latin American MFIs that is the largest group of the sample selected (212 observations). Looking at the mean values of MTBCE, it is interesting to note that Asian MFIs that claim the lowest mean FE value under group technology are replaced by African MFIs that however show the highest mean FE value with respect to its group frontier. In other words, although African MFIs show the highest FE (0.61) with respect to the group frontiers, the score considerably changes to 0.18 when we consider the metafrontier. This indicates that the output vector is 61% of the maximum output that could be produced on average when MFIs in the same region are compared, and that output is 18% if the maximum output if the metatechnology is considered. Moreover, when consider the OE under the metafrontier, Asian MFIs show the highest average OE whereas MFIs in Eastern Europe show the lowest. Overall, the comparison of mean efficiency scores under group and metafrontier technologies emphasizes the importance of model specification for MFIs operating in different geographical regions. The last panel of the table 6 deliver calculated MTR for MFIs in each region. Results reveal that MFIs in Asia have the highest MTR for both financial and outreach dimensions with average of 0.981 and 1, respectively. This means that MFIs in Asia financially and socially operate close to the metafrontier. The average MTR value of 1 for OE indicates that MFIs in Asia is equally efficient in terms of poverty outreach with respect to both group and metafrontier. On the contrary, the lowest mean MTR for FE and OE shown by MFIs located in Africa and Eastern Europe, respectively. African MFIs are on average producing 28% of their potential output taking into account their inputs and consequently, their potential improvement is estimated at 72% on average. On the other hand, the average MTR for MFIs in Eastern Europe (0.223) suggests that East European MFIs could produce 22.3% of the output that could be produced using the same inputs and metatechnology. Thus, their average potential improvement is estimated at 77.7%.

INSERT TABLE 6 HERE

4.3 Second-stage results

Table 7 presents the estimated bias-adjusted coefficients for FE and OE estimates. Note that following Simar & Wilson (2007), we use the confidence interval for hypothesis testing to determine whether estimated coefficients are statistically significant or not. If the value of zero does not fall within the confidence interval, then the corresponding measure is statistically significant. To preserve space, we do not report the confidence intervals, but these are available on request.

Since some variables can be highly correlated, we first test for multicollinearity of the all independent and control variables using the Variance Inflation Factor (VIF). Following the thumb rule that VIFs of all regressors should be less than 10 (see Cohen et al., 2003), we find no multicollinearity between environmental variables (mean VIF = 1.17). We also conduct a robustness test by rerunning the control variables in two different ways. We examine whether the variables that are significant in the model 1, still remain significant after dropping those insignificant variables as presented in model 2. All statistically significant environmental variables in the model 1 have the same directions in model 2 confirm the robustness of our findings.

The results concerning the relationship between MFI age and efficiency estimates are mixed. The coefficient concerning the relationship between new MFIs and financial efficiency is not significantly different from zero suggesting that new MFIs make no effect on financial efficiency. However, coefficient for young MFIs (YOUNG) remains negative and statistically significant with financial efficiency suggesting that older MFIs perform better than younger ones in terms of achieving financial results. This result is congruent with the results of Caudill et al. (2008), Wijesiri et al. (2015) and Lebovics et al. (2014). A possible explanation for this result might be that MFIs may take reasonable time period to capture the market. It is commonly acknowledged that mutual understanding and trust between an MFI and its clients are very important factors for the success of an MFI, especially for those which adopt group lending methodology and this takes time (age) to grow. The negative relationship between financial efficiency and age is, therefore, an indicator of the presence of learning by doing effect in the industry. This result may also be explained by the fact that as MFIs age, some of them tend to transform into different legal forms (for example from NGO to a NBFI), that allow them not only to widen the range of products including savings services that are usually more important to poor clients than lending (Vogel, 1984) but also to diversify their ownership and governance structure, improve the management information systems and improve the transparency and efficiency (Ledgerwood & White, 2006). With respect to the relationship between new MFIs and OE, we find no evidence that new MFIs make significant effect on MFI outreach efficiency. However, positive and statistically significant correlation between young MFIs and OE suggests that mature MFIs are relatively inefficient in their outreach objectives. This finding is consistent with Wijesiri et al. (2015) who argue that as MFIs age, they tend to diversify their portfolio towards to the less poor. Consistent with Hartarska & Nadolnyak (2007), SIZE contributes positively to both financial and outreach efficiency, suggesting that larger MFIs are more efficient in terms of financial sustainability and poverty outreach. The reason can possibly be attributed to the ability of larger MFIs to reduce the costs from economies of scale. Another possible explanation for this positive relationship is that larger MFIs may use more sophisticated technologies (i.e., advanced management information system, teller machines, online transactions, mobile banking) and their ability to diversify products and services (i.e. savings mobilization, remittance, insurance, leasing) through well-established branches network to improve the financial inclusion in more cost effective way, compared to smaller MFIs that depend on time and labor consuming outdated methods. This finding could also be due to the fact that large MFI become a large one because repeat borrowers tend to take out increasingly larger loans (for example Bank Rakyat Indonesia allowed doubling the loan value each year provided the prior loan was repaid promptly). Hence, the client credit worthiness is well known to the MFI, it requires less screening cost per loan and even much less per dollar of outstanding loan portfolio, the larger loan is clearly more profitable product than the past smaller one as higher income is received and cost per dollar lent are reduced. On the other hand, information asymmetry between a larger MFI and its clients could be very low as larger firms have higher society's awareness that eventually lead to reduce agency costs (Nhung & Okuda, 2015). In general, this finding is in line with the casual empiricism theory that argues that small financial institutions are more likely to fail (Wheelock & Wilson, 2000). Considering control variables, it is clear that estimated coefficient for CU dummy variable exhibits significant and positive relationship with financial efficiency. However, this relationship is significant and negative with outreach efficiency suggesting that credit unions are more market oriented. These results may be due to the fact that credit unions are being member service organizations cater to people with a common bond, not necessarily the poor (Hamed, 2007) and often they tend to lend less risky, middle-class salaried borrows (Robinson, 2001). With regards to the coefficients for NBFI dummy variable, it is positive and significant with financial efficiency implying that NBFIs are more financially efficient. However, the negative and significant relationship between NBFI and OE suggest that NBFIs are not efficient in terms of reaching to the poor. As shown in the table, the estimated coefficient for BANK dummy variable is significant and positive with financial efficiency implying that banks are financially more efficient compared to NGOs. On the other hand, significant and negative coefficient for BANK dummy variable with outreach efficiency suggests that banks are inefficient in outreach to the poor compared with NGOs. This finding is in line with Gutierrez-Niéto et al. 2009; Servin et al., 2012 and Barry & Tacneng, 2014. In general, the positive correlations between financial efficiency and all ownership types excluding NGOs, may attributable to the fact that different financing options including savings mobilizations available to them. In other words, compared with NGOs that are not allowed to accept public deposits, regulated MFIs that have a large savings value as a % of total loan portfolio are likely to have a different production function (e.g. lower cost of capital because interest paid on saving is lower than interest paid on unsubsidized loans but also relatively higher administrative cost resulted from handling saving services) and tend to operate more efficiently. On the other hand, we find a positive and significant relationship between NGO and outreach efficiency, suggesting that NGOs are more effective in terms of achieving social objectives. This finding confirms the earlier findings (e.g., Gutierrez-Niéto et al. 2009; Wijesiri et al., 2015) and consistent with the view that NGOs put more weight on social objectives (Morduch, 1999; Servin et al., 2012). As concern the ROA, it is clear that ROA exhibits positive and statistically significant relationship with financial efficiency. This positive effect of ROA on financial efficiency may reflect the fact that more profitable MFIs tend to have higher financial efficiency. This finding is also consistent with the view that in order to achieve financial sustainability, MFIs have to be financially more efficient. However, the coefficient concerning the relationship between ROA and outreach efficiency is not significant suggesting that financial performance measured by ROA makes no effect on outreach efficiency. This finding is in line with Gutiérrez-Nieto et al. (2009) and Lebovics et al. (2014). The reason for this is not clear but it perhaps can be explained by the notion of donor expectations. In real life some donors expect and push MFIs to go for more poverty impact (Balkenhol, 2007) despite the fact, that higher operating costs per dollar lent are involved. In such a situation, subsidies fuel them to set their outreach objectives, irrespective of whether they are profitable or not. Thus, it seems that profitability and social efficiency do not necessarily go hand in hand. The coefficient concerning the relationship between DER and financial efficiency is negative, but not statistically significant. This suggests that DER does not exert any perceptible bearing on financial efficiency. On the other hand, DER shows a negative and statistically significant relationship with outreach efficiency suggesting that MFIs with higher outreach efficiency, ceteris paribus, uses less debt financing. One possible reason for this negative relationship is that debt financing is not common in MFIs that focus more on mitigating poverty as some commercial lenders are reluctant to lend for such highly risky business. This result also indicates that when an MFI just start operating, it may be financed only by a grant that is converted to equity followed by donor's underscoring and preferring working on outreach aspects primarily, only when they grow and "prove" themselves they might become a candidate for borrowing. With regard to the REGION dummy variables, they all show negative and statistically significant relationship with financial efficiency and positive and statistically significant with outreach efficiency. This result suggests that MFIs in Latin America (LA), Asia (ASIA) and Africa (AFRICA) are financially inefficient but efficient in terms of outreach to the poor. MFIs in Eastern Europe (EE), on the other hand, show an opposite relationship. Though financially efficient, they are inefficient in terms of poverty outreach. This finding is in line with the findings of Gutierrez-Niéto et al. (2009). Note that the same substantive findings with model 2 confirm that results in model 1 are robust.

INSERT TABLE 7 HERE

5. Conclusion, research implications and future research agenda

When we feed back our findings to the more theoretical observations discussed in the introduction, we can make the following comments.

This study advances the literature on MFIs efficiency by investigating the impacts of age and size simultaneously along financial and depth of outreach efficiency dimensions. Because the sample of MFIs in our study is from several geographical regions, estimating a single frontier for the whole sample assuming that all MFIs use the same technology is likely to result in biased efficiency estimates. Thus, we use a metafrontier model that takes into account any heterogeneity between MFIs operate in different regions in the comparison of efficiency scores. We use the bootstrapped DEA method proposed by Simar & Wilosn (1998, 2000) to construct the metafrontier model and subsequently obtain bias-corrected efficiency scores. Then, bias-corrected efficiency scores are regressed on age, size and several control variables using the double bootstrap truncated regression approach proposed by Simar & Wilson (2007).

Our results highlight the importance of model specification for MFIs operating in different geographical regions. Moreover, we find that although older MFIs perform better than younger ones in terms of achieving financial goals, they are relatively inefficient in achieving their outreach objectives. Additionally, we find, not surprisingly, size of MFIs matters: the bigger MFIs that may have more assets, staff, clients and more credit lines tend to have higher financial and outreach efficiencies. Collectively, our findings support the view that it is old and large MFIs that are more likely to be allowed to mobilize voluntary savings than young and small ones and consequently become more efficient in terms of financial intermediation and addressing demand for savings that is highly appreciated by savers.

Findings of this study make reliable and up-to-date policy conclusions that would be of importance to a number of interested groups. Since efficiency reflects on and are affected by the policy decisions (Mukherjee et al. 2002) understanding the impact of age and size on both dimensions of efficiency estimates helps policy makers to evaluate the strengths and weaknesses of current policy choices. Moreover, identifying how age and size influence on both dimensions of efficiency is of utmost importance for incumbent MFIs and perhaps more importantly for NGOs that think of setting up microfinance programs to design viable business models to compete and join the better performers in the increasingly becoming crowded market. Additionally, donors who have a growing interest in financial and social performance of MFIs within which they could evaluate whether the funding support is warranted, can use the findings of the present study to design viable mechanisms that are directly linked to clear quantifiable milestone achievements of financial sustainability and outreach of target clientele.

In qualifying our conclusions, we recognize following caveats and research implications in our study.

I. Because of paucity of available time-series data for individual MFIs, we conduct this empirical study based on a sample of cross-sectional data. Thus, the present study does not acknowledge the shifts in the frontier of MFIs in response to changes in regulatory and technical instruments in the market.

II. Given the data availability, we use total assets to measure MFI size. Use of total assets as a proxy for MFI size would be more appropriate in the context of financial model. However, we believe a measurement of the size based on the number of clients seems more relevant in the outreach model. Thus, future research adding the size in number of clients may provide new insights on the impact of the size variable on MFI performance.

III. While our sample drawn from MIX has several strengths, it also has some weaknesses. Data available in MIX are reported voluntarily and in most cases financial ratios are systematically, only partially adjusted for subsidies compared to what they should. For example, financial performance of MFIs as measured by ROA and the widely- used Financial Self-Sufficiency (FSS) as presented in MIX publications suffer from two basic distortions that usually result in presenting 'adjusted' ROAs that underestimate subsidies received by the MFI, or alternatively put, presenting higher financial sustainability than the actual one as elaborated in Manos and Yaron (2009b). First, the shadow prices used by MIX to charge the average annual equity of the MFI (that is a cost free item in accounting terms) is the annual inflation rate. No investor, whether private or public would agree to accept zero return on equity measured in real terms as an adequate return. Hence, the real cost of equity is higher than the inflation rate and in developing countries it is usually much higher. Therefore, the lower is the DER ratio the higher is the subsidy ingredient which is not captured by the ROA that MIX presents. Second, MIX applies the deposit interest rate prevailing in the country concerned, as the shadow price for concessionary borrowing of the MFIs, instead of the lending rate (plus an often needed upward adjustment). This practice clearly underestimates subsidies received by the MFI and overstates financial sustainability.

IV. There are a number of studies that use production frontier methods to determine a possible trade-off between outreach and sustainability. While some studies (e.g., Hermes et al., 2011; Abate et al., 2013) reveal a trade-off between increasing outreach to the poor and gaining financial sustainability, some others (e.g., Gutierrez-Nieto et al., 2009; Mersland & Strom, 2010) conclude that both complement each other. One of the major reasons for these inconclusive and ambiguous findings is that these studies use efficiency as a criterion to measure the sustainability. In the context of microfinance, "financial sustainability" refers to ability of MFIs to operate free from subsidized inputs (Morduch, 1999). For example, Conning (1999) writes "In most discussions sustainability is taken to mean full cost recovery or profit making, and is associated with the aim of building microfinance institutions that can last into the future without continued reliance on government subsidies or donor funds". There are a large number of MFIs across the world that relies on various levels of subsidies to cover their costs (Quayes, 2012; Piot-Lepetit & Nzongang, 2014) and some of which can be fully efficient as subsidies can improve the MFI efficiency (Hudon & Traca, 2011). For example, our results show that some MFIs are fully efficient when compared to its peers. Though fully efficient, some of them could be highly subsidized as much of the success of microfinance has been dependent on the role of continuing subsidies (Morduch, 1999). Thus, this finding does not necessarily mean that those MFIs that lie on the constructed frontier are sustainable (or subsidy independent). We, therefore, wish to claim that relying on only efficiency scores yielded from production frontier methods is not adequate to determine the existing of either compatibility or trade-off between MFI dual objectives. Instead, applying jointly the production frontier and the SDI methodologies could upgrade evaluation and measurement of MFIs' efficiency, their financial performance and subsidy dependence, thereby generating improved understanding of their actual benefits and costs- a prerequisite for meaningful and effective support granted to the MFI industry. Applying these methodologies would also allow useful comparison with the benefits and cost of other poverty reducing instruments that also aspire to enhance the welfare of the same target clientele, could improve resource allocation and better use of public funds as well as facilitate linking support to MFI to achieving of measurable objectives of outreach, financial sustainability and efficiency. Thus, future investigations using data for multiple years and using jointly the production frontier and the SDI methodologies would be an important extension to the present paper.

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Table 1

Observations by age and size and operating region of MFI

Variable	Asia	Latin America	Africa	Eastern Europe
Age				
New	4	4	5	2
Young	32	19	12	0
Mature	100	189	27	26
Total	136	212	44	28
Size				
Small	31	56	11	7
Medium	60	98	21	15
Large	45	58	12	6
Total	136	212	44	28

Table 2

MFIs in example

MFI	Standardized average loan balance per borrower (K)	Number of active borrowers	Number of women borrowers
X	20	1500	1500
Y	15	500	250

Table 3

Main descriptive statistics for variables used in this study

Variable	All MFIs	MFIS (Asia)	MFIs (Latin America)	MFIs (Africa)	MFIs (Eastern Europe)
OPEX' 000					
Mean	11,301	10,371	12,193	13,080	6,263
Std. dev.	24,089	20,482	25,769	31,244	11,040
Personnel					
Mean	610	1,030	386	661	179
Std. dev.	1,452	2,252	702	1,117	240
GLP' 000					
Mean	92,708	129,838	78,784	74,545	46,031
Std. dev.	346,883	528,469	205,182	274,023	108,139
Revenue' 000					
Mean	2,078	24,018	20,334	19,864	9,937
Std. dev.	50,134	57,923	45,952	56,970	19,493
ALB					
Mean	6.88	6.31	8.40	3.28	3.77
Std. dev.	8.53	5.74	10.42	4.17	6.03
AB'000					

Mean	135	319	44	77	18
Std. dev.	576	979	94	153	28

Note: OPEX = Operating expenses; GLP = Gross loan portfolio; ALB = Standardized average loan balance per borrower (inverse value); AB = Number of active borrowers

Table 4

Input and output variable definitions

Variable	Unit	Definition
Operating expenses	US$	Expenses related to operations, including all personnel expense, depreciation and amortization, and administrative expense.
Total number of employees	Number	The number of individuals who are actively employed by MFI.
Gross loan portfolio (GLP)	US$	All outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off. It does not include interest receivable.
Financial revenue	US$	Revenues from the loan portfolio and from other financial assets are broken out separately and by type of income (interest, fee).
Standardized average loan balance (inverse value)	Number	Average loan balance per borrower/ GNI per capita
Number of active borrowers	Number	The number of individuals who currently have an outstanding loan balance with the MFI or are primarily responsible for repaying any portion of the GLP.

Note: All definitions are compiled from MixMarket database, accessed in April, 2015 (http://www.mixmarket.org/about/faqs/glossary)

Table 5

Hypothesis test of return to scale

	Financial Model	Outreach Model
Test Statistic (S)	0.79	0.83
Critical Value	0.75	0.56

Table 6

Summary statistics for the financial efficiency (FE), outreach efficiency (OE) obtained from the group frontiers and the metafrontier production function and MTR for MFIs in Asia, Latin America, Africa and Eastern Europe. The bootstrap estimates are produced using 2000 bootstrap replications.

Descriptive Statistics	Asia		Latin America		Africa		Eastern Europe	
	FE	OE	FE	OE	FE	OE	FE	OE
GTOE								
Mean	0.2719	0.3504	0.4254	0.3717	0.6619	0.3728	0.6824	0.5180
Std. dev.	0.2390	0.3022	0.1990	0.2068	0.2084	0.3059	0.2124	0.2694
GTBCE								
Mean	0.2227	0.3047	0.3923	0.3275	0.6159	0.2849	0.6006	0.4301
Std. dev.	0.1822	0.2595	0.1740	0.1683	0.1918	0.2204	0.1694	0.2140
GTCI								
LB	0.1945	0.2709	0.3605	0.2964	0.5628	0.2410	0.5393	0.3690
UB	0.2579	0.3415	0.4202	0.3607	0.6588	0.3501	0.6705	0.5058

MTOE								
Mean	0.2614	0.3504	0.3539	0.1687	0.1902	0.1506	0.3565	0.1185
Std. dev.	0.2198	0.3022	0.1781	0.1177	0.1036	0.1186	0.1492	0.0863
MTBCE								
Mean	0.2135	0.2908	0.3238	0.1484	0.1795	0.1332	0.3224	0.1076
Std. dev.	0.1862	0.2443	0.1490	0.0966	0.0980	0.1053	0.1194	0.0745
MTCI								
LB	0.2132	0.2551	0.2995	0.1326	0.1679	0.1194	0.2967	0.0972
UB	0.2550	0.3337	0.3465	0.1648	0.1881	0.1466	0.3475	0.1164
MTR								
Mean	0.9816	1.0000	0.8245	0.4459	0.2803	0.4720	0.5235	0.2226
Std. dev.	0.0488	0.0000	0.0383	0.0862	0.1053	0.1382	0.1159	0.0668

Table 7

Truncated bootstrap second stage regression

Variable	FE		SE	
	Model 1	Model 2	Model 1	Model 2
Constant	-0.9971***	-1.0072***	0.9737***	0.7711***
New	0.0534	0.0548	-0.1219	-0.0945
Young	-0.1235**	-0.1257**	0.0831**	0.0849**
Size	0.0000009***	0.0000009***	0.0000011***	0.0000011***
CU	0.2871***	0.2863***	-0.0965**	-0.0967**
NBFI	0.0907**	0.0906**	-0.0595*	-0.0581*
Bank	0.2665***	0.2666***	-0.2941***	-0.3009***
ROA	1.3713***	1.3667***	-0.2102	
DER	-0.0002		-0.0042**	-0.0042**
Latin America	-0.0975*	-0.0970*	0.1565**	0.1566**
Asia	-0.2309***	-0.2311***	0.2666***	0.2630***
Africa	-0.4339***	-0.4297***	0.2075***	0.2108***

(***), (**), (*): statistically significant at 1% , 5% and 10% respectively; total number of iterations = 2000