Commercialisation and Efficiency of Microfinance Institutions in Sub Saharan Africa

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Abstract

With the proliferation of microfinance institutions (MFIs) in Sub Saharan Africa (SSA) and the increased focus on the efficient way to extend microfinance services to the unbanked segment of the poor population, this paper examines the efficiency of MFIs in SSA countries for the period 2005 – 2011 through Data Envelopment Analysis. Again, the study uses truncated regression model to ascertain the effect of the current move for commercialisation of MFIs on their efficiency. It also investigates the effect if any, of the recent global financial crisis on the observed efficiency levels of these institutions. The findings indicate that the overall technical efficiency scores over the sample period range from 0.1003 to 1, with an average figure of 0.6288. Decomposing overall technical efficiency (OTE) into pure technical efficiency (PTE) and scale efficiency (SE), the average PTE and SE estimated is 0.6921 and 0.9124 respectively. This suggests that most (about 30.79%) of the overall technical inefficiencies (37.12%) observed within SSA microfinance industry is due to managerial inefficiency with little source of scale inefficiency. Furthermore, the results demonstrate that compared to non-commercial MFIs, scale inefficiency is predominantly high among commercial MFIs while managerial inefficiency is high among non-commercial MFIs. With regards to the drivers of efficiency, we found strong positive effect of commercialisation and age of MFIs (a measure of experience) on both OTE and PTE, whereas urbanisation and the recent global financial crisis worsened the efficiency of these institutions.

Key Words: Commercialisation, Efficiency, Microfinance Institutions, Sub Saharan Africa

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1. Introduction

The concept of extending financial access to the poor for economic activities following their exclusion from access to traditional commercial banks has been referred to as microfinance. The institutions involved in the provision of microfinance were initially set up as not-for-profit organisations (also known as Greenfield banks) such as NGOs to provide products and services customised to meet the financial needs of the poor. In view of the social objective of these institutions, their activities were largely financed with grants and subsidies. Besides, they were largely unregulated in the countries in which they operate and this hindered them from access to commercial funds.

In spite of the success stories of many microfinance institutions (MFIs) in improving the living conditions of many poor households in developing countries (e.g. Mckernan, 2002 and Khandker, 2003), it is estimated that about 40% to 80% of the population in most developing countries still have unmet demand for financial services (Cull et al., 2007; World Bank, 2008). Out of a total demand of about \$50 billion, only 4% is met by MFIs. This is largely due to funding problems faced by these institutions from their donor partners to meet their on lending activities (Bystrom, 2007). Many investors are reluctant to finance the activities of microfinance institutions, mainly because these institutions are said to lack the professionalism, are small in size, have weak balance sheet, no regulation, lack good governance and clear ownership and are less profitable investment projects (Tulchin, 2004).

In an attempt to overcome these challenges, many have suggested that the microfinance industry should be commercialised. The proponents of this movement argue that commercialisation of microfinance will widen the pool of funds available to MFIs in order to expand their outreach to the poor (Daley-Harris, 2009). They further argue that in order to attract money from investors for their continued poverty alleviation objective, MFIs will have to play by the rules of formal financial institutions. These rules require that MFIs pursue profitability and ultimately attain full commercial status (Cull et al., 2008; Counts, 2008).

Commercialisation of MFIs has become a dominant policy focus in most part of the world today, especially in Latin America. This is with the view of obtaining commercial funding from investors to ensure large scale outreach to the world's poor population who still have no access to basic financial services². A recent report on the microfinance industry in Sub Saharan Africa (SSA) indicates that commercialisation is taking place within the sub region. Thus, the SSA microfinance industry has not

² See Dacheva (undated: 7) for a detailed discussion on commercialisation of microfinance

been set apart from the global trend. Governments of almost all countries within the sub region have enacted laws and regulations to ensure successful commercialisation of MFIs. These regulations have encouraged the creation of profit seeking MFIs with the ability to seek commercial funding such as deposit taking, equity and loans from investors (MIX and CGAP, 2011).

In view of this transformation within the microfinance industry, the operating environment for the MFIs in SSA has changed significantly. They are faced with increased competitive pressures and varying customer demands. These include microcredit, micro-savings, micro insurance, micro leasing among others. As a result, MFIs have been prompted to bring changes in their operational strategies in order to ensure efficiency in their operation and continual growth. Besides, competition within the industry forces MFIs to reduce or maintain their cost of operation while improving the quality of their services both in terms of outreach to the poor and achieving sustainability.

As the microfinance industry in SSA continues to develop at a rapid pace, it has become important for these institutions to remain efficient in their production process so that they can withstand the forces of competition and succeed in a changing global environment. In view of this, we have carried out this research with the main objective of examining the technical efficiency of the microfinance industry in SSA for the period 2005 – 2011. Moreover, we intend to investigate into the most influential factors determining the efficiency of these institutions. The objectives of this study is therefore in three folds: i) to estimate the overall technical (OTE), pure technical (PTE) and scale efficiency (SE) of the microfinance industry in SSA; ii) to ascertain whether the move of MFIs from non-commercialised to commercialised institutions pave way for more efficiency; and iii) to determine if the recent global financial had any effect on the observed efficiency levels of these institutions.

To achieve the underlined objectives of this study, we relied on the most recent data on 273 SSA MFIs from Microfinance Information eXchange (MIX) market database, for the period 2005 – 2011 from 35 countries. In addition, we employed a two stage sequential estimation technique. Using Data Envelopment Analysis (DEA) we estimate the OTE, PTE and SE in the first stage. These estimates were then used to examine the extent of OTE, PTE and SE in SSA. In the second stage, we investigate the determinants of OTE and PTE using truncated regression model.

The findings from the study can be summarised as follows. First and foremost, it was established that overall technical efficiency of SSA microfinance industry is quite moderate, ranging from 0.1003 to 1, with an average score of 0.6288. Secondly, most of the overall technical inefficiencies (about 30.79% of 37.12%) observed were largely to due to inappropriate management practices being followed by the

managers of MFIs (i.e. due to managerial inefficiency). Nonetheless, compared to non-commercial MFIs, scale inefficiency was higher among commercial MFIs whereas managerial inefficiency is higher among the former institutions. From the multivariate regression analysis, we found robust results to support the assertion that commercialisation improves efficiency through the pursuit of profitability and regulation. In addition, the age of MFIs (a measure of experience) has a non-linear effect on technical efficiency while urbanisation and the recent global financial crisis worsened the observed efficiency levels of these institutions.

The remainder of the study is organised as follows. The next section provides a review of the literature on efficiency of microfinance institutions while the third section focus on the data and methodology employed for the study. The forth section provides the empirical results and discussions. This is followed by conclusions and policy recommendations in the last section.

2. Relevant Literature Review

There have been quite a number of studies on the efficiency of microfinance institutions. But, most of these studies differ in their definition of efficiency, estimation methods and the potential determinants of efficiency. For example, Lafourcade et al. (2005) used cost per borrower and cost per saver as a measure of efficiency of 165 SSA MFIs from 25 countries. They do this using a cross sectional data from MIX market database for the year 2003. Compared to global peers, they found that Africa MFIs have the highest cost per borrower of \$72 but with the lowest cost per saver of 8% of GNI per capita. Furthermore, the study observed that regulated MFIs maintain high efficiency through low cost per borrower and per saver. Besides, African cooperative MFIs are the least efficient with the highest cost per borrower, but the most efficient with the lowest cost per saver.

Gonzalez (2007) on the other hand, examined the effects of both institutional and country level variables on the efficiency of MFIs worldwide. The author used an unbalanced panel data of 1,003 MFIs in 84 countries for the period 1999 – 2006. The author considered the operating expensive ratio of an MFI in any given period as the measure of efficiency. He found that the main institutional level variables that positively determine the efficiency of MFIs were average loan size relative to GNI per capita, age of the MFI and gross loan portfolio relative to assets. With regards to the country level variables, he found a positive effect of the electricity production per capita on operating expense ratio, but a negative effect of percentage of roads that are paved on operating expense ratio.

The above studies considered the contribution of a single factor input to a single output as a measure of efficiency. However, using one input to evaluate performance amounts to ignoring the contribution of other inputs in the production process (Ray and Chen, 2009). In view of the nature of operation of MFIs and their dual objective of reducing poverty through outreach to the poor and achieving institutional sustainability, we need an aggregate measure of all inputs and outputs to express productivity as the ratio of the weighted outputs to that of inputs. This will require the use of non-parametric Data Envelopment Analysis (DEA), which is the estimation technique used in this paper.

Nghiem et al. (2006) also analysed the efficiency of the microfinance industry in Vietnam through a survey of 46 microfinance schemes using three different estimation techniques to the measurement of efficiency. These are Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA) and Parametric Linear Programming (PLP). Their results indicate that the average technical efficiency scores of surveyed microfinance schemes was about 80%. With regards to the determinants of efficiency, their analysis revealed that the age of the institutions and their locations in the country where they operate were the most significant factors influencing efficiency.

Likewise, Hermes et al. (2009) sought to find out whether the level of financial development of a country in which an MFI operates has an effect on their efficiency. They apply both SFA and DEA to the measurement of technical efficiency on an unbalanced panel data of 435 MFIs for the period 1997 – 2007 worldwide. Using different measures of financial development, their findings indicated that financial development has a positive impact on efficiency through competition. The authors further noted that MFIs efficiency is also determined by the type of loans they provide, their age, outreach (measured by the average loan balance per borrower or percentage of women borrowers) and size of the MFI (measured by the number of active borrowers).

Tariq et al. (2010) made a similar finding by examining the efficiency of Indian MFIs and their determinants by using SFA on an unbalanced panel data of 40 MFIs from the period 2005 - 2008. Their study revealed that the mean efficiency of MFIs in India for their sample period was quite low, estimated at 0.34, but increased over the study period from 0.257 in 2005 to 0.401 in 2008. Besides, the study identified the age of the MFIs and outreach (measured by the number of active borrowers) to be the main drivers impacting positively on efficiency of MFIs whereas regulated institutions were found to be less efficient. Haq et al. (2010) on the other hand, using both production and

intermediation approach³ to measure efficiency, examined the cost efficiency of 39 MFIs which provide 50% of their financial services (mainly loans and deposits) to poor households across Africa, Asia and Latin America for the year 2004. They found that NGOs are the most efficient MFIs under production approach while Bank MFIs outer perform their counterparts in the measurement of efficiency under intermediation approach.

Following the earlier works of Nghiem et al. (2006) and Hermes et al. (2009) which examined the efficiency of MFIs using both SFA and DEA, Annim (2010) employed a balanced panel data of 164 MFIs in 64 countries across Africa, East Asia and Pacific, Eastern Europe and Central Asia, Latin America and the Caribbean, Mediterranean and South Asia for the period 2004 – 2008 to examine the patterns and trend of efficiency of MFIs as well as the relationship between Operational Sustainability and pure technical efficiency levels. The results indicate an existence of complementarities between sustainability and efficiency. In addition, by dividing efficiency and outreach, whereas the latter improves social efficiency. Furthermore, the results indicate a negative effect of bureaucracies in property registration and lack of credit information in a country on the social efficiency of MFIs.

More recently, Oteng-Abayie et al. (2011) analysed the economic efficiency of 135 MFIs in Ghana and its determinants for the period 2007 - 2010 using SFA. Their results show efficiency scores ranging between 0.0712 - 0.7992, with an average score of 0.5629. With regards to the determinants of efficiency, they found that the total savings, cost per borrower, age, average loan balance per borrower, average saving balance per saver are significant determinants of efficiency. However, apart from average saving balance per saver which was negative, all the other coefficients were positive. Kipesha (2012), on the other hand employed input oriented DEA model to ascertain the efficiency of 35 MFIs in Eastern Africa for the period 2009 - 2011. It was found that the average technical efficiency was generally due to pure technical inefficiency resulting from misallocation of inputs in the production of outputs.

The empirical literature concerning the effect of commercialisation and the recent global financial crisis on the efficiency of MFIs is rather non-existent. Nonetheless, some individuals have expressed their views regarding the relationships between these variables. Commercialisation of microfinance is

³ The production approach considers MFIs as factory producing services to the poor households while the Intermediation approach considers MFIs as financial institutions intermediating funds between savers and investors at the least cost.

defined as the movement out of heavily donor-dependent arena of subsidising the operations of MFIs into one in which these institutions are integrated into the regulated financial system (Christen and Drake 2002, p. 4 in Ledgerwood and White, 2006)⁴.

Ledgerwood and White (2006) note that an MFI can become commercialised either through transformation of an existing not-for-profit MFI into a regulated financial institution that can mobilise savings from the public or to create a commercial MFI from scratch. Another notable path to commercialisation in microfinance the authors observed is for commercial banks to become involved in microfinance activities. They further argued that, the main reasons why MFIs choose to transform to become commercialised are to offer additional products and services (particular savings) to their customers and to gain access to capital (both debt and equity) and in so doing expand their outreach to the poor. Besides, transformation to a regulated deposit taking financial institutions enhances governance and ownership structure leading to more efficient and sustainable institutions.

Commercialising MFIs has received numerous opposing views. The critiques believe that excessive profit orientation associated with commercialisation will push interest rates up and prevent potential borrowers from access to loans. Moreover, they argue that commercialisation can crowd out credit supply to the poor because serving wealthier clients is often more profitable than serving the poor (Woller et al., 1999). While the current study does not seek to validate the above criticisms, we wish to ascertain the effect that commercialisation will have on the efficiency of the MFIs. Our position in this paper is that for these MFIs to be able to expand financial access to large numbers of the world's poor population they must be efficient in their production process.

More recently, Kiweu (2012) in his book, "*Commercialisation of Microfinance in Africa: Tapping the financial markets for microfinance, an empirical approach*", sought to investigate the factors that ensure success in commercialising microfinance institutions in Africa. Using factor analysis procedures on a surveyed questionnaire administered to 117 microfinance experts, the author identified the critical success factors to commercialisation of microfinance to be the extent of MFI formalisation and transparency in financial reporting, sound financial management and good governance, operational reputation and stage of development of the institutions.

Given the above underpinnings, this paper examines the effect of commercialisation of microfinance on technical efficiency of MFIs. As a result, we ask the question, does the regulation and profit seeking

⁴ Many researchers have argued that subsidy dependence creates inefficiencies which prevent growth of institutions

behaviour associated with commercialisation within the microfinance industry pave way for more efficiency? Also, we wish to ascertain whether the recent global financial crisis could have any effect on the efficiency of microfinance institutions in SSA. The rationale for this consideration is that the crisis affected the economies of several countries in many ways. In SSA for example, overall GDP in the region deteriorated to 1.6% in 2009, from 5% in 2008 (World Bank, 2010). Nonetheless, whether these observed effects of the crisis could have any spill-over effects on efficiency of the microfinance industry is not too clear.

In addressing the impact of the current financial crisis on microfinance in an interview, Bernard Balkenhol, the chief of International Labour Organisation (ILO) on social finance programme states that: *"It depends largely on the way microfinance institutions raise their resources. Cooperative organised microfinance institutions use primarily member deposit, while NGOs work mostly with grants and soft loans. Microfinance banks for their part are refinanced on market conditions or at concessionary rates and if they are authorised to do so, they collect member deposit. These different types of financial resources transmit the crisis differently." He concluded that <i>"The more a MFI is integrated itself into the commercial financial market, the more it is now exposed to the fall-out from the crisis"* (ILO, 2009). There has been little attention to examine the aforementioned claim within the microfinance literature. Chen et al. (2010) observed that in the latter part of 2008 and early 2009, portfolio quality and growth of MFIs in four countries (Pakistan, Nicaragua, Morocco and Bosnia and Herzegovina) deteriorated in comparison to the period between 2005 and 2007⁵.

Similarly, the Consultative Group to Assist the Poor (CGAP) in March 2009 conducted an opinion survey on about 400 MFI managers worldwide to monitor the impact of the global financial crisis. The survey responses revealed that MFIs and their clients are being hurt by the crisis. On the clients' side, the managers (about 69%) reported that there has been deterioration in loan repayments resulting from high food prices and drops in clients' income due to the financial crisis. On the MFIs side, liquidity issues and credit risks were the biggest managerial concerns. Nonetheless, about three quarters of the MFI managers interviewed were optimistic that their performance will remain stable or improve over the next six months after the period of the survey.

Based on the reviewed empirical studies on the efficiency of MFIs, this paper contribution to the existing literature is in three folds. First and foremost, we wish to estimate the overall technical (OTE),

⁵ However, the author could not established whether the recent global financial crisis is a primary cause of the deterioration observed

pure technical (PTE) and scale efficiency (SE) of the microfinance industry in Sub Saharan Africa (SSA) based on output oriented DEA model. Secondly, we wish to ascertain whether the move of MFIs from non-commercialised to commercialised institutions pave way for more efficiency. Lastly, the study aim to determine if the recent global financial had any effect on the observed efficiency levels of these institutions. These investigations bring to the forefront some empirical newness and are also vital for policy modelling and discourse. The next section provides information on the data source and discusses methodology used for the study.

3.1 Data Source and Sample Size

The data for this study is extracted from the Microfinance Information eXchange (MIX) market database on SSA countries. MIX is a US based not-for- profit organisation established in 2002 to provide a worldwide online based microfinance information platform. It provides detailed information on financial, operational and social performance of MFIs worldwide. The study relies on an unbalanced panel data of 273 MFIs covering the period of 2005 - 2011 in 35 countries (see a description of the panel in Table 1).

[Insert Table 1]

3.2. Theoretical and Empirical Models for the Study

The approach to measure the productive efficiency of any Decision Making Unit (DMU) quantitatively, also known as the frontier analysis is first developed by Farrell (1957). He categorises efficiency into two components. These are technical efficiency (TE), which measures the success of a DMU of producing the maximum output with a given set of inputs and allocative efficiency (AE), which denotes the success of a DMU in choosing the optimal combination of inputs. The latter requires information about the input prices while the former involves only input and output quantities or values. The frontier analysis deals with the estimation of the relative efficiency scores of various DMUs with common inputs and outputs in a given sample then compared the efficiency of a unit with that of the best performing units in the sample.

Subsequently, the approach by Farrell (1957) was extended by Aigner et al, (1977), Meeusen and Van den Broeck (1977) into what is known as the parametric frontier efficiency measurement (called Stochastic Frontier Analysis). Farrell's idea of efficiency measure was again extended by Charnes et al, (1978) into a nonparametric frontier efficiency measurement approach of Data Envelopment Analysis (DEA). These two approaches (i.e. parametric and nonparametric) have been widely used for efficiency measurement in several academic fields in the literature. This study relies on the use of

DEA and follows a two stage approach to examine the efficiency of MFIs in Sub Saharan Africa. The ensuing paragraphs provide reasons for the use of DEA and the estimation strategies.

First, unlike SFA, the DEA model has the ability to incorporate multiple inputs and outputs easily in estimating efficiency scores of DMUs. Thus, its use becomes relevant for a study of this nature owing to the dual objective nature of microfinance institutions. Secondly, it does not require restrictions on the observed data set through the impositions of a functional form as required by parametric approaches. (Tariq et al, 2008). Nonetheless, the use of DEA has been criticised because of its deterministic property. The critics argue that it ignores measurement errors, omitted variables and exogenous shocks in the measurement. Hence it assumes that variations in firm performance obtained from the first stage of calculating the efficiency scores are all attributed to inefficiency (Simar and Wilson, 2007).

It is worth mentioning that in DEA, input oriented or output oriented production models are assumed. Input oriented DEA models concentrate on reducing the amount of inputs by keeping output constant in order to operate on the frontier while output oriented DEA models focus on maximising the amount of output with given levels of inputs in order to be on the frontier. This study assumes that an output oriented DEA production model is best suited for assessing the performance of MFIs⁶. The purpose of an output oriented DEA model to the measurement of efficiency in this study is to evaluate by how much output quantities can be proportionally increased without changing the input quantities used.

Therefore guided by the literature and intuition, the following inputs and outputs variables were deemed appropriate for estimating the efficiency scores. The inputs used are personnel expenses, administrative expenses and financial expenses while the outputs used are financial revenue and net loans. Unlike other studies, the dollar amounts of the inputs rather than the quantities are used in this study to capture the effects of both the quantity and quality of the inputs in producing the outputs. Secondly, we used net loans (i.e. gross loans less bad loans⁷) rather than the gross loans portfolio as a measure of output. This is to control for a situation where it may be easier to give out loans than to recover them, particularly when some MFIs may not be so much concerned about their own efficiency

⁶ This is because of the MFIs dual objective of increasing outreach (through granting more loans to the poor) and attaining institutional/financial sustainability (by mobilising more revenue from lending). Therefore the operational definition of efficiency as used in this study is producing the maximum outputs with given level of inputs.

⁷ We used part of the loan portfolio that is long overdue for 3 calendar months (90 days) as a proxy for bad loans

and sustainability (Table 2a provides the definition of the variables used in estimating the efficiency scores).

[Insert Table 2a]

Furthermore, the literature assumed that the production function of any DMU (e.g. MFI) may differ over time and space depending on the assumption underlying the returns to scale of the production function. That is whether it is constant return to scale (CRS) or variable returns to scale (VRS). This study assumes VRS version of the DEA model. The reasons for these are: CRS has an implicit assumption that all DMUs are functioning at an optimal scale. However, the heterogeneity of MFIs operational and loan delivery strategies and their different inclination to any of the dual objectives may undermine the relevance of the CRS assumption that all institutions operate at their optimal scale. Again, the VRS version of DEA allows us to decompose the estimated Overall Technical Efficiency (OTE) scores into Pure Technical Efficiency (PTE) and Scale Efficiency (SE). Disaggregating efficiency into PTE and SE therefore facilitates attribution of inefficiency to implementation lapses (or managerial inefficiency) and size of operation respectively (Annim, 2010).

In the first stage of the estimation, it is assumed that there are N MFIs, each with m number of inputs (X) and s number of outputs (Y). The relative efficiency score of a particular DMU j is obtained by solving the following model proposed by Charnes et al. (1978).

$$Max \ \theta_0 = \frac{\sum_{i}^{s} u_r Y_{ro}}{\sum_{i}^{m} v_i X_{io}}$$
(1)
Subject to $\frac{\sum_{i}^{s} u_r Y_{rj}}{\sum_{i}^{m} v_{ij} X_{ij}} \le 1 \ ; \lambda_r \ge 0 \text{ and } \alpha_i \ge 0$

Where θ_0 is efficiency measure of a particular MFI whose efficiency score is being estimated and that of all other MFIs is denoted by the subscript j ; j = 1, 2, 3, ..., N

 Y_{rj} is the observed quantity of output r produced by the jth MFI; r = 1, 2, 3, ..., s

 X_{ii} is the observed quantity of input i used by the jth MFI; i = 1, 2, 3, ..., m

 u_r and v_i are the respective output and inputs weights to be determined by solving the above equation.

Equation (1) means that the efficiency of any MFI is defined as the ratio of weighted outputs to weighted inputs subject to the conditions that the ratios for every MFI is less than or equal to one. The maximum value of the efficiency score, θ for any MFI can only be a positive number less than or equal to one. If the efficiency score, θ of any MFI is equal to one, then that MFI satisfies the necessary condition to be DEA efficient, otherwise it is inefficient. Equation (1) is a non-convex non-linear programming problem. To reduce it to a linear form, Charnes et al, (1978) impose the restriction $\sum_{i}^{m} v_{i}X_{i0} = 1$. This therefore reduces equation (1) to:

 $Max \theta_{j} = \sum_{r}^{s} u_{r} Y_{ro} \qquad (2)$ Subject to $\sum_{r}^{s} u Y_{rj} - \sum_{i}^{m} v_{ij} X_{ij} \le 0$

Equation (2) also means that an MFI's objective is to maximise outputs subject to inputs and with the condition that virtual outputs cannot go beyond virtual inputs for any MFI. Besides, equation (2) deals with the constant returns to scale version of the DEA model. However, to estimate the variable returns to scale version of DEA, we adopt the extended model developed by Banker et al (1984) which is defined as:

$$Max \theta_j = \sum_r^s u_r Y_{ro} - u_0$$
(3)

Subject to $\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_{ij} X_{ij} - u_0 \le 0$

Where u_0 which is part of the optimal solution problem and produced by the computer code measures the return to scale possibilities. If $u_0 = 0$, then DMU₀ has a constant returns to scale characteristic. Otherwise, $u_0 > 0$ implies decreasing returns to scale and $u_0 < 0$ implies increasing returns to scale.

Owing to the drawback of the use of DEA mentioned earlier, this study employs the use of bootstrapping techniques suggested by Simar and Wilson (2007) in the second stage of the study to examine the determinants of efficiency. The next section presents the empirical model for determining the efficiency drivers.

3.3 Truncated Regression Model for estimating the determinants of Technical Efficiency of MFIs

After estimating the technical efficiency of each MFI for each of the years across the sample period for the study in stage one, we now take another step in examining the efficiency of the MFIs in Sub Saharan Africa by looking at their potential determinants. The coefficients of interest together with other control variables are estimated using the truncated regression model. Compared to OLS, this model has the strength of estimating equations whose dependent variable values are restricted within some range and therefore yield unbiased estimates (Akaeli, 2008). The empirical model for the study is specified as:

$$\theta_{jt} = \beta_0 + \beta_1 \text{Commercial}_{jt} + \beta_2 \text{Age}_{jt} + \beta_3 \text{Agesquare}_{jt} + \beta_4 \text{Charter}_{jt} + \beta_5 \text{office}_{jt} + \beta_6 \text{Rural Pop. growth}_{jt} + \beta_7 \text{Unban Pop. growth}_{jt} + \beta_8 \text{GDPgrowth}_{jt} + \varepsilon_{jt} - \dots (4)^8$$

Where θ_{jt} denotes the technical efficiency level of the jth MFI in period t. Commercial_{jt} is a measure of commercialisation characterised by both the profitability and regulatory status of the jth MFI in period t. Both are dummy variables which indicate whether the jth MFI is a profit entity or not and whether its activities are regulated by any given authority such as the central bank or not. Age_{jt} denotes the age of the jth MFI in period t. The inclusion of this variable is to ascertain the effect of experience on technical efficiency.

Again, to control for MFI specific features, we include (1) the charter type which indicated whether an MFI is classified as Rural Bank, Credit union/Cooperatives, Non Governmental Organisations (NGOs), Non Bank Financial Institutions (NBFIs) or Bank and (2) the number of offices an MFI has in a given period. Furthermore, we used both the rural and urban population of the county in which the jth MFI operate in period t to examine the effect of the population requesting for microfinance services on the efficiency of MFIs. Lastly, we include the GDP growth of the economy in which the jth MFI operate in period t, to ascertain the effect of the health of an economy on institutional efficiency. Table 2a in the Appendix provides the definition of the explanatory variables used and their hypothesised relationships with the efficiency scores. The next section presents a discussion of the results obtained from the study.

4.0 Results and Discussions

This section presents the empirical results obtained from the study. The data were analysed using STATA version 12 and the results have been put into three main sections. The first section provides a description of the inputs and output variables used in estimating the technical efficiency scores while the second section contains a discussion on the observed efficiency levels of the MFIs in Sub Saharan

⁸ We performed Pooled regression by splitting the sample in two groups. These are period before the global financial crisis (2005 - 2007) and period during the crisis (2008 - 2011). The rational for this is to test whether there is a structural change in the model due to the global financial crisis.

Africa. The last section contains a discussion on determinants of technical efficiency of these institutions.

4.1. Descriptive Statistics of inputs and output variables used in estimating the Technical Efficiency scores

The analysis in this paper is based on 273 MFIs from 2005 – 2011 that consist of 149 not-for-profit MFIs and 124 profit MFIs. Table 2a and Table 2b provide the definition and summary statistics of the inputs and output variables used in estimating the technical efficiency scores of the MFIs across the sample period. We found that the indicators of inputs measured by personnel expenses, administrative expenses and financial expenses are on average relatively higher for the profit MFIs than not-for-profit MFIs. Also it is evident from Table 2b that the amount of loans granted and revenue mobilised by profit MFIs are relatively higher than that of not-for-profit MFIs⁹. A parametric, t- test conducted on the mean difference of the inputs and outputs variables between the two groups of MFIs revealed significant difference in the mean values of the inputs and output variables. This means that profits MFIs are able to grant more loans and also mobilise enough revenue than not for profit MFIs. In addition, compared to the not-for-profit MFIs are more efficient in utilising their inputs than not-for-profit MFIs cannot be deduced from this preliminary findings. The subsequent sections of the paper provide estimations and further discussions on the above findings from the descriptive statistics.

[Insert Table 2a and 2b]

4.2.1 Examining the Efficiency of Microfinance Institutions in Sub Saharan Africa

This section discusses the results of the technical efficiency estimates obtained from the use of output oriented DEA model. We obtained the relative technical efficiency scores of the MFIs for each of the seven years (2005 – 2011) considered for the study. Table 3 provides the frequency distribution and descriptive statistics of the overall technical efficiency (OTE), pure technical efficiency (PTE) and scale efficiency (SE) scores for the entire sample period. It can be observed from Table 3 that the OTE scores range between 0.1003 and 1, and its mean and standard deviation are 0.6288 and 0.2063 respectively. This means that the average level of overall technical inefficiency is about 37.12 percent. We can therefore infer that between 2005 and 2011 the microfinance industry in SSA could have increase their levels of outputs by 37.12 percent with the existing level of inputs by efficient utilisation

⁹ This finding confirms the report by MIX and CGAP (2011) that although not-for-profit MFIs dominates the microfinance industry in SSA, profit MFIs account for over 70% of total loan portfolio as well as the fastest growth in outreach.

of these inputs. In addition, we observe the presence of significant variations in Overall Technical Inefficiency (OTIE) for the period under review. The highest and lowest levels of OTIE have been noted for MED-NET MFI (89.97 percent) in Cote d'Ivoire and MCA MFI (1.19 percent) in Cameroon respectively¹⁰. Moreover, the frequency distribution of the OTE scores indicated that about 79 percent of the observations had efficiency scores below 0.8 with only about 10 percent considered to be fully efficient (i.e. with OTE scores equal to 1). This means that overall technical inefficiency is substantially high within the microfinance industry in SSA. The sources of overall technical inefficiency can be due to ineffective implementation of the production plan by managers of MFIs in transforming inputs to outputs (known as pure technical inefficiency) and/or due to the divergence of MFIs from the most productive scale size (called scale inefficiency).

[Insert Table 3]

To ascertain the sources of overall technical inefficiency (OTIE) in SSA, we decomposed overall technical efficiency (OTE) into two components, namely pure technical efficiency (PTE) and scale efficiency (SE). Table 3 also contains the frequency distribution of the PTE and SE scores together with their descriptive statistics. The mean value of PTE scores has been observed to be 0.6921 with a standard deviation of 0.2143. Besides, the PTE scores ranges from 0.1020 to 1. It can be concluded that the pure technical inefficiency within the microfinance industry in SSA during the period under review is about 30.79 percent. These results imply that about 30.79 percentage points of 37.12 percent of overall technical inefficiency identified above within the microfinance industry in SSA is largely due to inappropriate management practices that are being followed by the MFIs' implementers or managers in producing the optimal outputs with given level of inputs in their microfinance operations. The remaining part of the overall technical inefficiency is due to MFIs operating at sub-optimal scale.

Table 3 also shows the mean Scale efficiency (SE) for SSA microfinance industry from 2005 – 2011, which is quiet high being 0.9124 with standard deviation of 0.1055 and range from a score of 0.3841 to 1. The value of SE score equal to 1 means that the MFI is operating at most productive scale size (MPSS) which correspond to constant returns to scale while SE score less than 1 implies that an MFI is experiencing overall technical inefficiency because it is not operating at its optimal scale size. Besides, at MPSS, the institution operates at the minimum point of its long run average cost curve. The mean SE score of 0.9124 imply that the average level of scale inefficiency in Sub Saharan African microfinance industry is just about 8.76 percent. The implication of these observations is that,

¹⁰ A complete list of a table showing the technical efficiency scores for the MFIs spanning the period of seven years considered for the study can be provided upon request

compared to pure technical inefficiency (about 30.79%); scale inefficiency is not a major source of overall technical inefficiency in Sub Saharan Africa microfinance industry.

Furthermore, a glance through Table 3 indicates that out of 784 observations considered for the study, only 79 (10.08 percent) have been found to be overall technically efficient with OTE score equal to 1. These efficient MFIs together defined the efficient frontier of Sub Saharan African microfinance industry from 2005 to 2011¹¹ and thus represent the leading or best performing institutions, which forms the reference set for the inefficient MFIs. In addition, 140 (17.86 percent) observations have been found to be fully efficient under variable returns to scale since they have attained a PTE score equal to 1. Again, out of the 17.86 percent of fully efficient observations under variable returns to scale, 10.08 percent are also fully efficient under constant returns to scale assumptions with OTE score equal to 1. Thus, in about 7.78 percent of the observations, the overall technical inefficiency (OTIE) is caused by only scale inefficiency rather than managerial inefficiency. Among the overall technically efficient MFIs, these institutions: ACEP Senegal in Senegal, ASCI and DECSI both in Ethiopia, MECREF in Niger and MGPCC in Togo consistently remained efficient for more than three years. These institutions can therefore be considered as the leading performers within the sub region.

The return to scale characteristics of MFIs in Sub Saharan Africa (SSA) is also reported in Table 4. This is examined by the number of observations in the area of constant returns to scale (CRS), decreasing returns to scale (DRS) and increasing returns to scale (IRS). Out of the 784 observations, there are 394 observations which exhibit DRS, representing 50.26% of whole sample, while those falling under IRS and CRS account for 39.54% and 10.20% of all observations respectively. These results suggest that diseconomies of scale are prevalent within SSA microfinance industry. Nonetheless, there exists some scope for economies of scale, implying that some institutions (about 39.54% of the observations) have not reached their most productive scale size. Therefore expanding their production scale, for example through mergers and acquisition could lower their long-run average cost, promote profitability and increase market share.

[Insert Table 4]

¹¹ The geographical distributions of these efficient MFIs are: Middle Africa (6.33%), Eastern Africa (29.11%), Western Africa (60.76%) and Southern Africa (3.80%).

4.2.2 Comparing Efficiency Scores between Commercial and Non-commercial MFIs

Without disaggregating the data by profitability and Regulatory status of MFIs, we examined whether the observed efficiency levels differ between commercial and non-commercial MFIs. The results are shown in Figure 1. It can be observed from Figure 1 that the efficiency score for both groups of MFIs has not being quite stable overtime and also seems to follow the same pattern. Both groups of MFIs experienced a sharp decline in their OTE and PTE scores in the year 2008 but began to recover afterwards. With regards to overall technical efficiency, Figure 1 shows that commercial MFIs consistently remained better off than non-commercial MFIs. However, they were badly affected in the year 2008 compared to their counterparts. Considering the above results, this paper is interested in two questions: the first is whether commercialised MFIs are more efficient than non-commercial MFIs and secondly whether the decrease in the observed technical efficiency scores is caused by the 2008 global financial crisis. These are examined in a multivariate regression model in the next subsection of the paper.

[Insert Figure 1]

Furthermore, Figure 1 shows that commercial MFIs appear purely technically efficient than noncommercial MFIs whereas scale efficiency (SE) is higher among non-commercial MFIs throughout the sample period. This implies that most of the overall technical inefficiencies among commercial MFIs are due to the scale inefficiency rather than managerial inefficiency whereas the opposite can be said of non-commercial MFIs. Another remarkable finding is that compared to profit MFIs, about 42.76% of not-for-profit MFIs were at the stage of increasing returns to scale whereas majority (55.88%) of profit MFIs were at the stage of decreasing returns to scale. This means that there is tremendous scope of economies of scale for not-for-profit MFIs while most profit MFIs are operating beyond their optimal scale capacity, thus experiencing diseconomies of scale.

4.3 Investigating into the Determinants of Efficiency of Microfinance Institutions

This subsection discusses the estimates of the determinants of efficiency of MFIs in SSA for the period 2005–2011. Table 5 and Table 6 use Overall Technical Efficiency (OTE) and Pure Technical Efficiency (PTE) scores as the dependent variables respectively¹². We use the same independent variables in both estimates for the purpose of comparison. Specifically, we examined the association of the overall technical efficiency and pure technical efficiency scores with the commercial status of

¹² We did not report the regression results on scale efficiency because we could not reject the null hypothesis that the coefficients are jointly different from zero. This observation is not surprising given the fact that scale inefficiency is not a major concern in SSA microfinance industry

MFIs by controlling for firm specific and country level variables using the truncated regression model specified by equation (4). Furthermore, to ascertain whether the 2008 global financial crisis had any effect on the efficiency of MFIs in SSA, we split the sample into two groups: pre-crisis and crisis periods (i.e. period before the crisis and period during the crisis). Afterwards, we run separate regression on each of the sub-samples to test if there is any structural change in the parameters of the estimates.

Column B and C of Table 5 report the results on the determinants of OTE for the sample MFIs in SSA for the period before and during the global financial crisis respectively. We found that before the financial crisis commercial MFIs were more efficient than non-commercial MFIs by 9 percentage points. Though the coefficient of commercial status remained positive during the crisis period, compared to the pre-crisis period, the magnitude dropped by 0.8 percentage points to 8.2 percentage points. The coefficient of commercialised status dummy estimated in each of the two periods was highly significant at 1 percent. This finding is consistent with the view that commercial institutions with profit orientation are more efficient than not-for profit organisations¹³. However, they are more likely to be affected during financial crisis in view of their exposure to credit and liquidity risks¹⁴.

[Insert Table 5]

One of the robust results established in this study is a statistically significant non-linear effect of experience (measured by age and age square of MFIs) on OTE before and during the crisis period. We found a significant positive effect of age on OTE whereas the coefficient of age square was negative for each of the sample periods. This means that MFIs become more efficient as they grow older in the industry. However, the efficiency gain from experience diminishes after a certain stage in the life cycle of the institution.

With regards to the charter type of MFIs, we found that compared to rural banks, credit unions consistently remained the most efficient type of MFI in SSA before and during the financial crisis. Another interesting finding was that, during the crisis period rural banks were much worse-off in their OTE scores compared to their peers which saw an improvement in their efficiency scores during the

¹³ From our dataset, the average return on assets (ROA) between profit and not-for profit MFIs for the period 2005 - 2011 is -0.08 % and -2.77% respectively. These figures mean that managers of profit MFIs are more efficient in using their assets to generate earnings than managers of not-for profit MFIs.

 $^{^{14}}$ It is interesting to note that while the average return on assets for profit MFIs was positive before the financial crisis (1.37%), that of not-for profit MFIs was negative (-3.84%) during the same period. However, during the financial crisis, both had a negative average return on assets (-1.25% for profit MFIs and -2.07% for not-for profit MFIs).

crisis period compared to the pre-crisis period. It is not clear to us why rural banks were much affected by the financial crisis. However, the parameter estimate for credit unions is consistent with findings by Narter (2011) who compared efficiency ratios spanning a period between 2004–2010 for banks and credit unions and found that credit unions are consistently more efficient than banks. Among the reasons the author cited were that credit unions do not participate in commercial lending which is an inefficient part of banking. Besides, they have shared service centre, which enable more scale and greater efficiency. This observation is not too surprising because credit unions rely on members' deposits as the bigger share of their funding structure and hence have the lowest financial expense ratio. This finding is consistent with MIX and CGAP (2011) who found that in SSA, credit unions have a lower financial expense ratio of just 1.3% compared to NBFIs (3.6%) and NGOs (3.7%), hence most efficient than their peers.

Controlling for the size of MFIs, since efficiency may differ by the size of MFIs, we used the number of offices held by the MFIs. The results indicate that OTE of MFIs significantly improves as they expand their outreach through the establishment of more offices before the crisis. Nonetheless, the magnitude of this impact is not too huge (about 0.06 percentage points). Besides, the effect of office size on OTE disappears during the crisis period.

Another remarkable finding in this study relates to population growth of the economies in which the MFIs operate. Since the main objective of MFIs is to provide basic financial services to the unbanked segment of the world's population who are predominantly poor, the population growth variable is included in the regression as a proxy for the population requesting for microfinance services. We found a negative but not significant effect of rural population growth on OTE before the crisis period. Moreover, a 1 percent increase in urban population growth reduces overall technical efficiency by 3.21 percentage points at 5% level of significance before the crisis period. An interesting observation emerged during the crisis period. We found that at 1% level of significance, a 1 percent increase in either rural population growth improves overall technical efficiency by 3.23 percentage points. The implication of this finding is that if rural and urban population grows at the same rate, then urbanisation will worsen the efficiency of MFIs in the economies in which they operate.

Perhaps what could account for the above phenomenon is the view in the economic development literature concerning urban concentration. Richardson (1987) argues that the social investment cost of

absorbing an extra family in typical urban areas is threefold that of rural areas and even more for the largest city in a country. Henderson (2000) explained that in many countries, there is unequal development of infrastructure or provision of local public services across cities and that national government can choose to favour some cities over others, especially capital cities. Such favouritism results in migrants and firms flowing into the favoured cities until it become congested that the costs offset the advantages of the favouritism. Another possible explanation to the above observation is that, in rural areas, MFIs may face less competition from more traditional credit suppliers compared to operating in urban centres. This will enable them to enjoy economies of scale through expansion of credit access to many rural households were group lending methodology can easily to used to minimise operational costs.

Furthermore, we examine whether there is any spill-over effect of the growth of an economy on OTE of MFIs. Thus, we controlled for GDP growth and found that a 1 percent increase in economic growth increases OTE by 0.26 and 0.44 percentage points during the pre-crisis and the crisis period respectively. Nevertheless, these observations are not statistically significant at any reasonable level. To ascertain whether the 2008 global financial crisis had any effect on OTE of SSA MFIs, we test the joint hypothesis that the coefficient estimates during the pre-crisis and the crisis period are the same. We failed to accept the null hypothesis of no difference in the parameter estimates at 1% level of significance. The implication of this finding is that, there was a structural change in the OTE of MFIs in SSA due to the global financial crisis.

In terms of the determinants of PTE for SSA MFIs, we report the results in column B and C of Table 6 for both the pre-crisis and crisis periods respectively. Compared to the results obtained on the effects of the explanatory variables on OTE, we observed similar patterns for PTE before and during the global financial crisis¹⁵. We observed a significant positive effect of commercialisation of MFIs on PTE and non-linear effect of experience on PTE. Also, compared to rural banks, credit unions remained the most efficient MFIs followed by bank MFIs, NGOs and Non Bank Financial Institutions (NBFIs). While the number of offices has the expected sign, its effect on PTE is insignificant. With regards to the country level variables, we found that urbanisation reduces PTE of MFIs whereas economic growth improves PTE. Similarly, a hypothesis test on the difference in the parameter estimates of PTE between the pre-crisis and the crisis period proved to be highly significant at 1%.

¹⁵ It is important to mention that the variation in the number of observations for the two regressions is because of the fact that truncation drops observation that lies at the extremes. That is those institutions with efficiency scores of 1.

This means that the differences in the parameter estimates between the two sample periods can be attributed to the global financial crisis.

[Insert Table 6]

5. Conclusions

In this paper, we employed both Data Envelopment Analysis and truncated regression models to evaluate the extent of technical efficiency and its determinants in Sub Saharan Africa (SSA) microfinance industry respectively. Using an unbalanced panel data of 273 MFIs from MIX market database from 2005–2011, the results show some fluctuations in the levels of efficiency within the microfinance industry in SSA over time, and it reached its trough in the year 2008 after which it began to recover. The results demonstrate that overall technical efficiency scores across the years range from 0.1003 to 1, with an average figure of 0.6288. Thus, the level of overall technical inefficiency in SSA microfinance industry is about 37.12%. Disaggregating overall technical efficiency (OTE) into pure technical efficiency (PTE) and scale efficiency (SE), the average PTE and SE estimated is 0.6921 and 0.9124 respectively. This suggest that most (about 30.79%) of the overall technical inefficiencies (37.12%) observed within SSA microfinance industry is due to inappropriate management practices being followed by managers of MFIs, with little source of scale inefficiency. Furthermore, it is established from this study that the most leading or performing MFIs within the sub region are ACEP Senegal in Senegal, ACSI and DECSI both in Ethiopia, MECREF in Niger and MGPCC in Togo.

The results reveal that compared to non-commercial MFIs, scale inefficiency is predominantly high among commercial MFIs while pure technical inefficiency (managerial inefficiency) is high among non-commercial MFIs. The high managerial inefficiency observed for non-commercial MFIs can be attributable to lack of internal control and regulation to enhance efficiency among these institutions. This means that for non-commercial MFIs to upscale to commercial status in order to have the desired impact on pure technical efficiency, there is an urgent need to strength internal controls; improve governance and exhibit professionalism in their operations. Besides, the results relating to returns to scale indicate that 42.63% of not-for-profit MFIs in the sample are operating below their optimal scale, and therefore experiencing increasing returns to scale, while 56.05% of profit MFIs are operating beyond their optimal scale and therefore experiencing diseconomies of scale. From the return to scale possibilities of the MFIs, we can infer that substantial number of not-for profit MFIs are smaller in size. Therefore in order to take full advantage of economies of scale would require an expansion of these institutions in terms of scale size of their operations. However in view of the limited capital of

these not-for-profit MFIs and their dependence on grants and subsidies, one possible way this can be achieved is through merger/acquisition to increase market share and growth.

With regards to the drivers of efficiency, we found robust results to support the assertion that commercialisation improves efficiency through the pursuit of profitability and regulations. In addition, age of MFIs (a measure of experience) improves efficiency from initial stages of operation or establishment, but its effect diminishes with time. Controlling for the type of MFI, we found that compared to rural banks, credit unions consistently remained the most efficient MFIs in all specifications of the models used, followed by Bank MFIs, NGOs and Non-Bank Financial Institutions (NBFIs). Some efforts to understand the ways in which the management practices of credit unions differ from their peers could pay dividend for managers of the other categories of MFIs. Furthermore, the results suggest that size of institutions matter, with larger institutions being more efficient than smaller ones. Thus expanding access to microfinance through the establishment of more offices enhances efficiency.

It has also been established in this study that if rural and urban population grows at the same rate, then urbanisation will worsen the efficiency of MFIs. In most countries, MFIs tend to be concentrated in urban centres and districts with high population density due to favourable economic conditions in these areas. However, in this study we can argue that if the objective of microfinance is to be achieved, then the results of this study throw more challenges to microfinance operators such as commercial financial institutions which downscale to become involved in microfinance and non-commercial MFIs which upscale to commercial status. Thus, they should focus on targeting more rural population in order to make impact on the welfare of the low income households in these areas. This direction will not only improve the efficiency of MFIs but also prevent migrants who leave the rural to the urban areas to seek greener pastures. Furthermore, it is established in this study that the recent global financial crisis indeed slowed down the operations of microfinance institutions in SSA.

In view of the above research findings, we wish to emphasise that for SSA MFIs to become efficient and expand access to the poor or become more competitive in the global world, both internal control through governance and external regulation by supervisory authorities should be improved to instil fiscal discipline in the industry. This will reduce most of the managerial inefficiencies observed and also boost investors' confidence in the industry through access to commercial funding leading to sustainable institutions. Secondly, governments should maintain stable macroeconomic environment to boost private investment in microfinance especially to rural areas where poverty levels are high. Again we can infer from this study that, an insufficient investment in infrastructure such as road networks, electricity, public services among others, particularly in rural areas is more likely to lead to urbanisation and high concentration of MFIs in urban areas with no positive economic gains in efficiency. Therefore to be able to improve efficiency in microfinance operation, it is important that focus is geared towards measures aimed to improve the growth of an economy, most especially in the rural areas. This will provide the enabling environment for MFIs to operate more efficiently.

Future research on the efficiency of microfinance institutions in Sub Saharan Africa (SSA) seems to be very important for policy formulation. For example, it may be interesting to examine how or the channel through which the efficiency of MFIs in Sub Saharan Africa was affected by the recent global financial crisis. Moreover, an investigation into the inter-temporal variations in technical efficiency of MFIs in SSA will be essential. Thus, one could measure the total factor productivity (TFP) growth in SSA microfinance industry and decompose it into technical efficiency change and technological progress components using DEA-based Malmquist Productivity Index (MPI). However, this will require a balanced panel data.

APPENDIX

Year	Number of MFIs for which we have data in a	Number of
	particular year	Countries
2005	65	21
2006	124	25
2007	137	29
2008	152	30
2009	126	32
2010	108	27
2011	74	22
TOTAL	786	

Table 1: Description of the Panel (MFIs per year)

Source: MIX Market database

Table 2a: Definition of Variables used for the Study

Variables	Definitions	Apriori			
		Expectations			
Input Variables used in Estimating Efficiency scores					
Personnel Expense	This measures all personnel expenses related to operations in a particular period				
Administrative Expense	This includes expenses associated with maintaining premises or fixed assets (depreciation) and other expenses incurred in ensuring the day to day running of an MFI				
Financial Expense	This is the expense that an MFI incurs to fund its portfolio. It includes interest and fees expense on funding liabilities such as deposits and borrowings				
	Outputs Variables used in Estimating Efficiency scores				
Financial Revenue	This is the revenue an MFI obtains from its loan portfolio and other financial assets. Its includes interest, fees and commission on loan portfolio and other financial assets				
Net Loans	This is the gross loan of any MFI net of any loan loss provisions. This was derived as gross loans less portfolio at risk for 90 days (i.e. part of a loan portfolio which is deemed at risk because payments are long overdue). It is assumed that for any loan that has some amount in arrears, the total amount of the outstanding balance is at risk of not being repaid. MFIs calculate their loan loss reserve on the basis of this indicator				
Drivers of Efficiency		Efficiency Hypothesis			
Age of MFI	This is the number of years of an MFI since its establishment	+/-			
Profit Status	A dummy variable = 1 if MFI is registered as a profit making entity, zero equals otherwise.	+			
Regulation	A dummy variable = 1 if the activities of MFI is regulated by some authority such as the central bank, zero equals otherwise	+/-			
Charter Type	This indicates that category under which MFI is classified. It is used to classify the MFIs as banks, credit union/cooperatives, NGOs or non bank financial institutions (NBFIs).	+/-			
Office	This denotes the number of offices held by any MFI including head offices in any given period of time.	+/-			
Rural Population growth ^(a)	This defines the annual percentage growth in the population of people living in rural areas of a country in which MFI operate	+/-			
Urban Population growth ^(a)	This defines the annual percentage growth in the population of people living in urban areas of a country in which MFI operate	+/-			
GDP growth ^(a)	This measures the annual growth rate of the general economic conditions of a country in which an MFI operate	+			

Source: (a) – these variables were obtained from World Development Indicators (WDI), all other variables from MIX market database

	Not-for-profit MFIs			Profit MFIs				
Variables	Mean	Std.	Min.	Maxi.	Mean	Std.	Min.	Maxi.
Inputs varia	bles							
Personnel								
Expense	1,158.02	1,691.23	2.77	10,965.81	3,399.65	8,936.91	1.06	68,307.09
(in 000's \$)								
Administrat								
ive Expense	1,412.70	2,715.93	7.23	27,349.13	3,954.59	11,143.00	9.57	87,674.66
(in 000's \$)								
Financial								
Expense	461.95	855.43	0.0474	7,460.35	1,526.48	4,702.00	0.1731	53,573.51
(in 000's \$)								
Output Variables								
Financial								
Revenue	3,408.42	5,783.63	-205.79	47,119.58	13,121.13	41,932.29	11.06	372,773.50
(in 000's \$)								
Net Loans								
(in 000's \$)	11,199.37	22,237.21	10.16	182,203.20	31,201.58	108,238	62.43	1,244,074.0

Table 2b: Descriptive Statistics on variables used for Estimating the Efficiency Scores

Source: Author's calculation

Table 2c: Descriptive Statistics on the drivers of Efficiency

Variable	No. of Obs.	Mean	Std. Deviation	Min.	Maxi.
Age of MFI	784	11	7	0	44
Age square	784	174	239	0	1936
Profit Status					
(= 1 if for profit, 0 =	780	0.4346	0.4960	0	1
otherwise)					
Regulation Status					
(= 1 if Regulated, 0 =	775	0.7871	0.4096	0	1
otherwise)					
Commercialised					
(= 1 if for profit &	784	0.3788	0.4854	0	1
Regulated , 0 =					
otherwise)					
Rural Bank	784	0.0472	0.2122	0	1
NGO	784	0.2793	0.4490	0	1
Credit Union	784	0.2398	0.4272	0	1
NBFI	784	0.3291	0.4702	0	1
Bank	784	0.1046	0.3062	0	1
No. of Offices	776	31	50	1	363
Rural Population					
Growth	781	1.8375	0.6897	-1.3827	4.0731
Urban Population					
Growth	781	4.0592	0.9183	-0.5258	6.7043
GDP Growth	781	5.8003	3.2074	-4.7288	22.5931

Source: Author's calculation

Efficiency Scores	Overall Technical	Pure Technical	Scale Efficiency
(E)	Efficiency (OTE)	Efficiency (PTE)	(SE)
E < 0.5	212 (27.04%)	153 (19.52%)	1 (0.13%)
$0.5 \le E < 0.6$	160 (20.41%)	120 (15.31%)	12 (1.53%)
$0.6 \le E < 0.7$	163 (20.79%)	152 (19.39%)	34 (4.34%)
$0.7 \le E < 0.8$	85 (10.84%)	112 (14.29%)	63 (8.04%)
$0.8 \le E < 0.9$	52 (6.63%)	71 (9.06%)	162 (20.41%)
$0.9 \le E < 1.0$	33 (4.21%)	36 (4.59%)	434 (55.36%)
E = 1.0	79 (10.08%)	140 (17.86%)	80 (10.20%)
Descriptive Statistics of	the Efficiency Scores		
No. of observations	784	784	784
Mean	0.6288	0.6921	0.9124
Median	0.6080	0.6775	0.9521
Standard deviation	0.2063	0.2143	0.1055
Minimum	0.1003	0.1020	0.3841
Maximum	1.000	1.000	1.000

 Table 3: Frequency Distribution¹⁶ and Descriptive Statistics of Efficiency Scores (2005 – 2011)

Source: Author's own calculation.

Table 4: Returns to Scale Characteristics of MFIs

Category of MFI	Constant Returns to Scale	Decreasing Returns to Scale	Increasing Returns to Scale	Total observations
Profit MFIs	27 (7.96%)	190 (56.05%)	122 (35.99%)	339
		· · · ·	· · · ·	
Not-for-profit				
MFIs	53 (12.02%)	200 (45.35%)	188 (42.63%)	441
Tatal abarrations	90 (10 200/)	204 (50.260/)	210 (20 5 40/)	704
I otal observations	80 (10.20%)	394 (30.26%)	310 (39.54%)	/84

Source: Author's own calculation.

¹⁶ Figures in parenthesis are the percentages of observations that fall under each category of efficiency scores while figures outside the parenthesis indicate the corresponding number of observations.



Figure 1: Average Efficiency Scores between Commercial and Non-Commercial MFIs from 2005 - 2011





Source: Author's own calculation

Table 5: Determinants of Overall Technical Efficiency (OTE)

	[A] Full Sample	[B] Pro origin poriod	[C] Crisis pariod
Independent Variables	(2005 - 2011)	(2005 - 2007)	(2008 - 2011)
Commercial (=1 if for profit	0.0814***	0.0900***	0.0820***
& regulated, 0=otherwise)	(3.95)	(3.31)	(2.72)
Age (in years)	0.0124***	0.0157***	0.0113***
	(4.50)	(3.33)	(3.34)
Age Square	-0.0003***	-0.0004***	-0.0003**
	(-3.54)	(-2.65)	(-2.40)
Charter Type: Omitted Categor	ry, Rural Banks		
NGOs	0.0230	0.0207	0.1282***
	(0.72)	(0.53)	(3.20)
Credit Unions	0.0985***	0.0964*	0.2067***
	(2.83)	(1.93)	(4.70)
NBFIs	-0.0155	0.0024	0.0767**
	(-0.57)	(0.07)	(2.38)
Bank	0.0088	-0.0013	0.1192***
	(0.27)	(-0.03)	(2.91)
No. of Offices	0.0003	0.0006**	0.0000
	(1.49)	(1.98)	(0.05)
Rural pop. Growth	0.0259*	-0.0131	0.0434***
	(1.82)	(-0.55)	(2.60)
Urban Pop. Growth	-0.0363***	-0.0321**	-0.0323***
	(-3.81)	(-2.29)	(-2.62)
GDP Growth	0.0055**	0.0026	0.0044
	(2.31)	(0.61)	(1.eee
Constant	0.5156***	0.5915***	0.3573***
	(11.14)	(9.76)	(5.83)
/sigma	0.1693***	0.1551***	0.1698***
	(32.59)	(20.23)	(24.97)
Wald Chi2	90.26	44.48	66.07
Prob > chi2	0.000	0.000	0.000
Hypothesis Testing: ¹⁷		chi2 ((11) = 27.16
No. of Observations	607	200	$c_{1112} = 0.0044$
No. of Observations	697	290	407

Source: Author's Calculation. Z- values are in parenthesis and are based on 1000 bootstrap estimations of the truncated regression. Significance level of coefficients: * @ 10%, ** @ 5% and *** @ 1

¹⁷ We test the joint hypothesis that the coefficients between the two sample groups are the same

	[A] Eull Samula	[B]	[C] Crisis parisd
Indonondont Variables	Full Sample $(2005 - 2011)$	(2005 - 2007)	(2008 - 2011)
Commercial (=1 if for profit &	0.0815***	0.0943***	0.0798**
regulated. 0=otherwise)	(3.23)	(3.16)	(2.10)
	()	()	()
Age (in years)	0.0160***	0.0178***	0.0145***
	(5.32)	(3.81)	(3.51)
Age Square	-0.0004***	-0.0005***	-0.0003***
	(-4.43)	(-3.22)	(-2.70)
Charter Type: Omitted Category,	Rural Banks		
NGOs	0.0498	0.0390	0.1680***
	(1.47)	(0.94)	(3.46)
Credit Unions	0.1017***	0.0658	0.2359***
	(2.76)	(1.20)	(4.48)
NBFIs	0.0453	0.0507	0.1556***
	(1.49)	(1.47)	(3.91)
Bank	0.0934**	0.0696	0.2247***
	(2.51)	(1.66)	(4.66)
No. of Offices	0.0004**	0.0006	0.0003
	(2.06)	(1.53)	(1.25)
Rural pop. Growth	0.0132	-0.0322	0.0312
	(0.82)	(-1.29)	(1.60)
Urban Pop. Growth	-0.0339***	-0.0231	-0.0336**
	(-3.34)	(-1.47)	(-2.38)
GDP Growth	0.0059**	0.0010	0.0071**
	(2.15)	(0.21)	(2.09)
Constant	0.5060***	0.5904***	0.3416***
	(9.80)	(8.27)	(4.37)
/sigma	0.1741***	0.1555***	0.1798***
	(28.25)	(18.81)	(22.34)
Wald Chi2	91.88	13 76	74 99
Prob > chi2	0 000	0,000	0,000
Hypothesis Testing ¹⁸	0.000	chi? (11)) - 33.56
Trypomesis resulig.		Prob > chi	2 = 0.0004
No. of Observations	636	265	371

Source: Authors' Calculation. Z- values are in parenthesis and are based on 1000 bootstrap estimations of the truncated regression. Significance level of coefficients: * @ 10%, ** @ 5% and *** @ 1

¹⁸ We test the joint hypothesis that the coefficients between the two sample groups are the same

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