FIRM-SPECIFIC DETERMINANTS OF TECHNICAL EFFICIENCY IN MICROFINANCE INSTITUTIONS

Master thesis

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Abstract: In this study, I investigate the firm-specific determinants of technical efficiency in Microfinance Institutions (MFIs). By using stochastic frontier analysis as proposed by Battese & Coelli (1995), I draw from past research three key elements of MFIs – client outreach, ownership structure and institutional age – to examine whether the differences in technical efficiency of MFIs relative to their best production possibility frontier can be explained by these factors. The results show that technical efficiency can be enhanced through extending client outreach, measured by average loan balance and the percentage of female borrowers. Moreover, non-shareholder and experienced MFIs are more technically efficient. This study could prove useful to policy makers and microfinance practitioners in searching solutions to improve efficiency among MFIs while concerning the potential efficiency-outreach trade-off.

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I. Introduction

Microfinance has long been seen as an effective tool to provide financial access to poor families and microenterprises, who are unable to reach traditional banking services. The concept emerged in the 1970s, when Grameen Bank's first loan issued to a group of poor people in Bangladesh. According to Lützenkirchen (2012), Microfinance Institutions (MFIs) have successfully provided loans to more than 200 million unbanked clients around the world by the end of 2010. Mersland & Strøm (2010) in their research reveal that the industry growth has reached over 40% in 11 years from 1998 to 2008. The result shows a huge potential to enable broader financial inclusion, which plays a central role in alleviating poverty, empowering women and promoting economic growth (Cull, et al., 2014). Being regarded as one of the major innovations in the past 25 years, microfinance and its long-lasting contribution have attracted significant interest among academic researchers, governments, NGOs and individuals.

In 2008, microfinance experienced a serious setback, having seen excessive market growth while financial sustainability underestimated. Lützenkirchen (2012) reports that although MFIs had expanded greatly in terms of number of clients, they experienced an increasing trend in portfolio at risk 30, i.e. the portion of loans greater than 30 days overdue, from less than 3% in more than 5% within two years. The author also find that the negative correlation between market growth and portfolio quality from 2007 to 2009 was less likely due to the consequence of the global financial crisis but more of industry-specific problem. In some countries, for example the Indian state of Andhra Pradesh, private MFIs grew extensively, targeting at fast growth and heavy profits (C-GAP, 2010). The significant deterioration in portfolio quality in those MFIs prompted policy makers and microfinance practitioners to recognize the over-borrowing issue with imprudent monitoring in lending procedures and to search for new balance.

Several developments that demonstrate financial sustainability and efficiency, such as the commercialization in microfinance, prudent regulations and supervisions from banking authorities, are argued as solutions to deal with the above problems. The argument to support this concentration, the *financial systems* approach, states that MFIs' capability to serve the poor in long-term cannot be guaranteed unless they are financially efficient. The *poverty lending* approach, however, argues that there is a trade-off between outreach and efficiency because lending to the poor can be very costly (Robinson, 2001). The literature on this issue is not extensive (Hermes & Lensink, 2011) and much potential remains to expand our knowledge on such conflicting goals. This research attempts to contribute to the development of existing literature on microfinance efficiency by examining how these institutions can enhance the level of technical efficiency through their typical features, taking into account potential trade-offs that are likely to appear and may bring negative consequences as the institutions strive toward more technically efficient.

This study makes two specific contributions: First, in line with past research examining the current status of technical efficiency in MFIs, I examine the relationship between technical efficiency and rural outreach – proxied by average loan size and percentage of female borrowers (Hermes, et al., 2011; Gregoire & Tuya, 2006), and institutional age (Paxton, 2007). The trade-off between social outreach and efficiency among MFIs has been hotly debated among academic researchers. This issue is argued to be the result of numerous improvements in microfinance industry, including competition between MFIs, commercialization trend, technology changes, financial regulations and policies (Rhyne & Otero, 2006). Hermes, et al. (2011) provide empirical evidence showing that cost efficiency in MFIs has a negative correlation with the client outreach, measured by average loan size and portion of female clients. Meanwhile, Gregoire & Tuya (2006) find a positive relation between cost efficiency and average loan balance among MFIs in Peru. Gutiérrez-Nieto, et al. (2009) also find similar result in other regions such as Asia, Africa and East Europe, albeit insignificant. Thus, empirical evidence on the relationship between efficiency and the level of outreach of MFIs has been mixed. In this research, I focus on the technical efficiency and the corresponding level of client outreach, using extended data for the last 6 years and employing production frontier analysis as opposed to cost efficiency function used by previous studies.

Second, by employing production approach and considering an individual MFI as a producer of loans, investments and deposits, this study investigates the correlation between technical efficiency and ownership structure of MFIs. Servin, et al. (2012) show that MFIs in Latin America applying different ownership types use different technologies, hence possess different levels of efficiency. Specifically, differences in inter-firm efficiency suggest that banks and non-bank financial institutions (NBFIs) have higher technology efficiency than non-governmental organizations (NGOs) and cooperatives (COOPs). The reasons include the latter's concentration on social goals and more severe financial constraints. Moreover, intra-firm efficiency tests imply that NGOs and COOPs also achieve considerably lower efficiency with respect to their own frontiers, resulting essentially from dual objectives and the lack of appropriate incentive schemes. Yet studies that apply to other countries find contrasting results, such as Kumar & Sensarma (2015) examine MFIs in India; Haq, et al. (2010) study MFIs in Africa, Asia and Latin America or Hassan & Sanchez (2009) conduct research among MFIs in Latin America, Middle East and North Africa, and South Asia. The latter stream argues that non-shareholders institutions, NGOs and COOPs, are more efficient due to relaxation of regulation from banking authorities (Kumar & Sensarma, 2015); greater concentration on dual objectives of increasing outreach to the low-income (Haq, et al., 2010; Hassan & Sanchez, 2009). The aim of this study is thus to provide more comprehensive and updated empirical evidence of the relationship between technical efficiency and different ownership forms among MFIs in six regions.

Along with client outreach and ownership type, I use institutional age as the third variable to assess the level of technical efficiency in MFIs. Previous research has suggested that MFIs generally become more efficient as they grow thanks to the market knowledge gained from past experience (Caudill, et al., 2009; Paxton, 2007). However, empirical evidence provided by Gutiérrez-Nieto, et al. (2009) shows no relationship between two variables. Other studies, such as Hermes, et al. (2011) and Hermes, et al. (2009), argue that younger MFIs have higher efficiency compared to the mature group, resulting from the knowledge of the industry that has been built-in and broadly discussed among academic researchers, policy makers and practitioners. Besides, new entries with updated technological advances tend to catch-up quickly with the prevailing trends in the industry and hence are capable of leapfrogging the older counterparts. Therefore, including the years of operation of MFIs in assessing the level of technical efficiency gives some advantages both to provide new evidence on its effect and to control for size effects, as commonly noted in microfinance literature.

This work employs stochastic frontier analysis (SFA) as suggested by Battese & Coelli (1995) to estimate technical efficiency of MFIs in six regional groups. Unlike other parametric approaches that are commonly used in evaluating efficiency in financial institutions such as the thick frontier analysis and the distribution-free analysis, SFA allows an error term to capture measurement error and accounting irregularities that are inherent in data from developing markets (Paxton, 2007). The incorporated error term also ensures better assessment of two possible sources that cause the production to deviate from the best-practice production frontier – effects from external shocks and internal inefficiency (Coelli, et al., 2005). Technical efficiency in this study is examined through analyzing production function proposed by Aigner, et al. (1977) with composed error terms whose distributional assumption suggested by Stevenson (1980). Whereas past microfinance studies focus on cost efficiency and profit efficiency (Hermes, et al., 2011; Gutiérrez-Nieto, et al., 2009; Gregoire & Tuya, 2006; Hassan & Tufte, 2001), this study estimates the technical efficiency of MFIs. Servin, et al., (2012) argues that since good price information is often insufficient, profit and cost functions are generally difficult to measure. Moreover, because MFIs possess double objectives, namely financial and social sustainability, they should not consider maximizing profits as their pure goal. Technical efficiency rather requires that a MFI achieve the maximum quantities of outputs, given quantities of inputs (Kumbhakar, et al., 2015), thus provides more relevant context for MFIs.

In sum, this study targets at the following research questions:

Do firm-specific characteristics – rural outreach, ownership structure and institutional age – influence the level of a MFI's technical efficiency?

The results indicate that there is positive correlation between client outreach and technical efficiency. Particularly, reducing average loan size and increase the proportion of women in the total number of borrowers help improve technical efficiency in MFIs. Furthermore, non-shareholder and experienced MFIs are more efficient. The former feature implies the emphasis of dual targets among institutions in the pursuit of sustainability, while the latter suggests the advantages of market knowledge gained through learning by doing.

The remainder of the thesis proceeds as follows. Section 2 outlines the relevant literature background that underpins this research and formulates hypotheses. Section 3 presents research methodology. In Section 4, the dataset used in the empirical study will be described. Section 5 covers the empirical results and associated discussion. Section 6 outlines final concerns and recommendations for further research.

II. Literature Review and Hypotheses

2.1 The evolution of Microfinance

The idea of providing credit to poor households flourished during 1980s, associated with US economist Muhammad Yunus and the creation of Grameen Bank (Cull, et al., 2009). Before, low-income clients were unable to get access to traditional banking services due to their unqualified financial status, tiny loan amount demanded and lack of sufficient collateral. State-owned banks often held responsibility to serve the unbanked category, mainly focused on farmers. Problems arose in these government-run financial institutions as political imperatives, misaligned incentives and the risks associated with agricultural lending prevented the institutions from effectively reaching the poor (Conning & Udry, 2007). Yunnus started his lending experiments which targeted non-farm enterprises like handicraft shops and tortilla-making business. By launching pioneering models in developing countries like Bolivia and Bangladesh and achieving surprisingly successful outcomes, Yunnus gave hopes to millions of poor and very poor people to obtain small-scale loans, savings accounts, insurance and other financial services that were refused by traditional commercial banks (Armendáriz & Morduch, 2010). His idea of "microfinance" challenges decades of thinking about banking – finance and its relation with social change, because it can "unleash the productivity of cash-starved entrepreneurs and raise their incomes above poverty lines. It is a vision of poverty reduction that centers on self-help rather than direct income redistribution" (Cull, et al., 2009, p.167).

"Social businesses" built upon the core concentration on social missions have gained momentum in other countries since the success of Grameen Bank and led to a vast creation of microfinance institutions. The industry has encountered numerous changes along its massive growth. In 1990s, policy makers argued that MFIs should be profitable, given high repayment rates of borrowers. In this respect, donors encouraged MFIs to increase interest rates, strategically arrange modest subsidies and seek profits (Cull, et al., 2009). The goal to achieve commercial status combined with the original social mission urged MFIs to balance their social and commercial objectives and a long-term trade-off arose between these two goals (Hermes & Lensink, 2011). From 2007 to 2009, MFIs performance had gradually decreased: assets growth slowed significantly, net profits declined while portfolio risk rose (Lützenkirchen, 2012). During this period, a number of developments have made the industry become more diverse, such as institutions turning to commercial funding, rapid technology changes, financial regulation and supervision. Excessive profit-orientation in many institutions forced policy makers to bring back client focus at the core of MFIs operation and to search for a new "socio-commercial" approach in this fast-growing market.

Among important issues pointed out by (Hermes & Lensink, 2007), the question regarding sustainability versus outreach raises an important argument in considering the long-term development path of microfinance industry (Robinson, 2001). On one hand, the *financial systems* approach emphasizes the priority of financial sustainability in order for MFIs to stand on their own feet before reaching out to the poor. The reasons draw from the fact that granting credits to low-income customers requires more efforts and larger operational costs; and that MFIs capability to expand client outreach on a long-term basis cannot be complemented without maintaining financially efficient. The *poverty lending* approach, on the other hand, argues that poor customers cannot afford higher interest rates; thus more focus on financial sustainability would negatively influence the social goal of serving large groups of poor customers. There is convincing empirical evidence that the sustainability-outreach trade-off is existent (Hermes, et al., 2011;

Cull, et al., 2011b; Cull, et al., 2007). While acknowledging such potential conflict, the debate goes on in favor of the advocates of *financial systems* approach, as the main problem is not to consider which target should gain more attention, but to ask what the size of the trade-off that is still tolerable (Hermes & Lensink, 2011). One first attempt of addressing this issue is the study of Galema & Lensink (2011). Nonetheless, more empirically investigation is called for in analyzing the size of the trade-off before any clear conclusion can be achieved.

Another ongoing issue related to the development of the sustainability-outreach debate considers how a MFI could be more operationally efficient (Hermes & Lensink, 2011). From external-source perspective, past contributions include Hudon & Traca (2011) who examine the effects of subsidies on MFIs efficiency and find a positive relation, albeit up to a certain maximum level; Hermes, et al. (2009) who search for the impacts of country-level financial environment on MFIs efficiency. Other studies take the view from internal sources and focus on regional context: Gregoire & Tuya (2006) investigate the influence of average loan, assets size, financial leverage, business experience and portion of farm loans to the level of cost efficiency among MFIs in Peru; Abdulai & Tewari (2016) consider the relationship between total assets, operating expense to assets ratio, average loan balance per depositor, the percentage of female borrowers, the percentage of borrowers per personnel, and the MFIs cost efficiency; Paxton (2007) analyzes how semi-formal financial institutions in Mexico could improve their technical efficiency through initial investment in technology, change in average loan size, diversity among rural and urban customers, and through learning by doing; Servin, et al. (2012) attempt to explain the difference in the levels of technical efficiency of MFIs in Latin America from corporate governance perspectives. Obviously, a comprehensive empirical assessment is desirable to better understanding which and to what extent firm-specific characteristics affect the technical efficiency of MFIs across borders. The findings could be beneficial to policy makers in terms of searching ways to encourage MFIs operational efficiency through regulations, supervision and campaign. Microfinance practitioners would also find the results relevant in their decisions to further improve the efficiency of their operations.

2.2 Technical efficiency in banking systems

Academic research on evaluating the operational efficiency of traditional financial institutions provides some essential tools and methods to apply in the microfinance industry. Firstly, technical efficiency is perceived as an important criterion. Molyneux, et al. (2001) assert that higher efficiency can "lead to improved financial products and services, a higher volume of funds intermediated, greater and more appropriate innovations, a generally more responsive financial system, and improved risk-taking capabilities if efficiency profit gains are channeled into improved capital adequacy positions" (p. 9). Technical efficiency refers to the ability to maximize outputs given inputs (in case of output-oriented), or to minimize inputs given outputs (in case of input-oriented) (Lovell, 1993). Only quantities are taken into account, and no price information is considered (Kumbhakar, et al., 2015). Any inefficiency in practice that is resulted from suboptimal decisions related to input/output management (Bikker & Bos, 2008) drives the institution away from its production-efficient frontier, which portrays the optimal inputs/outputs mix (Berger, et al., 1993).

Secondly, the selection of sets of an institution's characteristics and environmental factors plays a crucial role in assessing the best-practice performance with which the institution's operation is compared (Hughes & Mester, 2010). Previous research investigating this issue includes Berger (2007), Bos, et al. (2005), Clark & Siems (2002), Mester (1997), Mester (1996) and Mester (1993). Although there is no general theory of performance that offers a solid framework, as suggested by Hughes & Mester (2010), typical firm-specific variables that are commonly taken into consideration include capital to assets ratio, numbers of branches, years of experience, managerial control, organizational form and several off-balance-sheet activities such as loan origination, loan commitments and lines of credit.

Finally, the level of technical efficiency seems sensitive to the estimation procedure used (Berger & Humphrey, 1997). There are several frontier techniques that can be used for efficiency estimates, although the results are varied across methods. The choice of which method to use depends in part on the construction of the frontier specification, the characteristics of the dataset to be estimated, and most importantly, whether there is explicit separation between the random error and the inefficiency effects related to the management practices.

2.3 Application of technical efficiency measures to MFIs

The microfinance industry is a special case of a formal financial market: it provides small loans and credits services to the low-income, and thus its interest is not purely generating profits. In turn, existing tools and frameworks that are widely used to assess the performance of traditional financial institutions may not entirely fit the new context (Gutiérrez-Nieto, et al., 2007). There are several papers focusing on *cost efficiency* in MFIs, including Hermes, et al. (2011), Gregoire & Tuya (2006), Hartarska, et al. (2006) and Hassan & Tufte (2001). These papers are driven by transaction cost minimization and stress the importance of financial viability in response to the big evolution of the industry. A consensus belief states that since lending to the poor is often costly, a sustainable MFI should generate enough income to cover its operational costs.

This research attempts to estimate *technical efficiency* in MFIs as motivated by the work of Servin, et al. (2012), who point out some relevant aspects of this concept in the context of microfinance. Firstly, cost and profit functions require price information of both inputs and outputs, which is often difficult to obtain from MFIs. Secondly, a MFI is assumed to pursue double objectives, which means profit maximization, as in spirit of *cost efficiency*, should not necessarily be the institution's central goal. Thirdly, information about the volumes of inputs and outputs, such as the number of loan accounts and the number of personnel, can be obtained from the MixMarket™ – (www.mixmarket.org). Finally, unlike traditional financial institutions that are assumed to be price takers, MFIs have at least some influence over setting interest rates and the costs of capital through lobbying. One caveat in using production model to examine the technical efficiency, however, is that input variables are assumed to be exogenous to address possible simultaneity issue.

Given the importance of the choices of firm-specific characteristics in determining the level of efficiency in the banking sector, I draw from past research three key elements and investigate their influence in the MFIs' technical efficiency. These are client outreach, ownership structure and institutional age.

2.3.1 Client outreach

Existing evidence of "mission drift" among MFIs, a tendency toward targeting wealthier clients to reduce operating costs (Cull, et al., 2007), has been convincingly shown by previous research (Cull, et al., (2011b); Hermes, et al., 2011; Galema & Lensink, 2011; Galema & Lensink, 2009). These papers propose several measures of mission drift, including average loan size, the percentage of female clients, the percentage of rural clients, and customers' poverty levels. The mainstream literature recognizes the existence of mission drift is drawn by cost-efficiency motivation (Serrano-Cinca & Gutiérrez-Nieto, 2014), that is, MFIs attempt to reduce operating costs and improve financial self-sufficiency by targeting high-repayment-rate clients, innovating lending contracts, increasing interest rates and fees. This line of research then draws the next question for further studies regarding the extent to which the size of such trade-off relationship is acceptable.

Still, the global empirical evidence of the negative relation is mixed. For example, Mersland & Strøm (2010) examine a broad MFI dataset and reveal no increase in average loan size, nor is the trend toward higher proportion of for-profit customers. Cull, et al. (2011a) suggest that social and financial targets are not incompatible, showing that for-profit lenders exhibit increase in profitability and outreach simultaneously. Likewise, Serrano-Cinca & Gutiérrez-Nieto (2014) in their research dataset find no evidence of mission drift, although indicate that in order to offset high operating costs from serving to the poorest fraction of customers, a MFI tends to charge higher interest rates and associated fees. This paper suggests that since higher interest rates burden the poor, a MFI can reduce these costs by employing Information and Communication Technologies, which has been successfully applied in the E-Commerce Industry. In NGOs and COOPs, their funding pressure combined with heavily social targets force them to opt for technology that offers more training to loan managers (Servin, et al., 2012), carry low-cost random audits and designs credit agent incentives to reduce information problems (Aubert, et al., 2009). In NBFIs and Banks, more relaxation in funding sources and stricter regulation enable them to further enhance efficiency through updating better technologies (Servin, et al., 2012). In any given context, a MFI is expected to pursue the most feasible technology type to accomplish predetermined goals and minimize trade-off.

This study follow the result of Mersland & Strøm (2010), who finds that average loan balance has not been reduced as MFIs increase their efficiency. This paper reveals that both average cost and average profit variables have positive effects on average loan, that average cost is more influential than the other, and that once a MFI can operate efficiently, it is able to lower average loan size and prevent mission drift due to counterbalancing effects between changes in average cost and in average profit. The study thus concludes that not only suspected mission drift went undetected in the test, but the MFIs tend to promote and even extend depth of outreach of average loan over time. This argument leads to the first hypothesis as states:

H1a. There is negative correlation between technical efficiency and average loan size.

Along with the average loan balance variable used as a proxy for the depth of outreach, the percentage of women in total customers is referred to as a measure of the breadth of outreach. The explanation for this alternative measure being favored among researchers is that using average value introduces some weaknesses in conclusion related to mission drift. Armendáriz & Szafarz (2009) point out that the existence of mission drift in operation of individual MFIs can be poorly recognized based on changes in average value: the MFI can increase loan size because of the interplay of its missions, or because of some regional characteristics that affect the heterogeneity of clientele. Another possible scenario is that those MFIs operating in countries that have a relatively small proportion of very poor households might be mistakenly perceived as deviating from social target. Dunford (2002) also argues that the average loan size criterion does not take into account the crucial importance of saving programs and other non-financial services to the very poor, hence fails to acknowledge the efforts of MFIs given to non-credit activities.

Therefore, in assessing the effects of client outreach, I follow previous research of (Cull, et al., 2009) to include the percentage of women in client portfolio of MFIs as a proxy indicator of the breadth of outreach. This inclusion is also in line with (Armendáriz & Vanroose, 2009) and (Agier & Szafarz, 2013) who show that women are among the core poor in many emerging economies, and so a measure to assess a MFI's social performance is related to gender. In this study, I investigate the extent to which an increase the number of female clients influences individual MFI's technical efficiency. The next hypothesis is developed as follows:

H1b. There is positive correlation between technical efficiency and the percentage of women in client portfolio.

2.3.2 Ownership types

Governance issues attract an increasing interest among academic researchers as a response to various developments in microfinance industry: the expanding financial services from microcredits to deposit offers, insurance and trainings; the shift in capital structure from government aids and subsidies to commercial funding. Ledgerwood (2013) and Galema, et al. (2012) classify MFIs into four different ownership types, including non-governmental organizations (NGOs), credit union/cooperatives (COOPs), non-bank financial institution (NBFIs) and banks/rural banks (Table 2.1). These forms differ significantly from those of traditional banking institutions and thus require better understanding of their roles and effects. But the consistency in findings about the relation of ownership structure and MFIs' performance has not been achieved. Mersland & Strøm (2009) argue that ownership type in general has no significant effect on MFIs' performance. On the contrary, Ledgerwood & White (2006) emphasize the importance of MFIs' transformation to for-profit ownership. The latter follows the logic of agency theory, but recognizes specific agency problems faced by MFIs: firm-customer relationship (Adams & Mehran, 2003) and donor-board relationship (Mersland, 2009).

Past studies addressing the relationship between ownership structure and MFIs' efficiency have not yet reach a consensus result. Haq, et al. (2010) shows that NGOs achieve a higher efficiency level in the role of the producers of loans and deposits. The study reveals that NGO-MFIs' high level of efficiency is drawn from off-balance sheet activities such as staff training, improved branch and distribution system; whereas Bank-MFIs experience somewhat less efficiency because of non-performing loans effects. These are in line with Gutiérrez-Nieto, et al. (2009) and Hassan & Sanchez (2009). However, Servin, et al. (2012) find contrasting results in which NGOs and COOPs, being perceived as credit suppliers, are less efficient in maximizing outputs due to lower level of technology and greater funding constraints. Perhaps the disagreement in these results depends in part on the selection of method used. Whereas the first three papers use non-parametric approach – Data Envelopment Analysis (DEA), the fourth one uses parametric approach – Stochastic Frontier Analysis (SFA). Each approach has both advantages and disadvantages in evaluating efficiency and will be briefly addressed in Section 3.

This paper contributes to the ongoing debate about the effects of ownership structure on the efficiency level among MFIs by extending previous research to include other regions in the research sample and applies the SFA to examine such relationship. The expectation from this investigation is in line with Haq,

Table 2.1: Different ownership types in MFIs

Legal form	NGOs	COOPs	NBFIs	Banks
Regulation	No	Partly	Partly	Yes
Objectives	Social and Financial	Social and Financial	Financial	Financial
Funding structure	Donations and subsidies	Deposits and debt	Equity and debt	Equity, deposits and debt
Ownership	No	Member	Shareholder	Shareholder
Services	Loans	Loans and Savings	Loans and micro insurance	Loans and Savings
Client type	Low-income	Depends on Members	Depends on product offering	Broad target and Small and Medium Enterprises

Source: Ledgerwood (2013) and Galema, et al. (2012)

et al. (2010), Gutiérrez-Nieto, et al. (2009) and Hassan & Sanchez (2009). That is, non-shareholder MFIs (NGOs and COOPs) observe higher technical efficiency than that of shareholder MFIs (NBFIs, Banks and Rural Banks). Unlike the latter group who puts high emphasis on financial goals, the former group takes into account both social and financial targets simultaneously when making strategic decisions. In evaluating the performance of these groups, the efficiency that relates to maximizing the number of loan products and associated credit services to the customers, especially the poor, is hence predicted to be higher among non-shareholder institutions. The second hypothesis is thus formulated as follows:

H2. Technical efficiencies in non-shareholder MFIs are higher than that of shareholder MFIs.

2.3.3 Institutional age:

More years of operation in field supports a MFI in improving efficiency through learning from past experience. Paxton (2007) and Gregoire & Tuya (2006) find that production variability reduces significantly as years of experience and scale of a MFI increase, implying an improvement in technical efficiency. Caudill, et al. (2009) also confirms the result by showing that older MFIs are more cost efficient through advanced lending technology, accumulated market information and concrete relationship with clients. While the formers use institutional age to assess the change in technical inefficiency proxied by the residuals from production function and cost function respectively, the latter inputs the variable directly to the cost function.

Competing results from Hermes, et al. (2011) and Hermes, et al. (2009) show that there is a negative correlation between a MFI's age and efficiency. They argue that older MFIs are less efficient because they have to constantly adapt new lending innovation and technology to cope with the dynamic of microfinance industry. Meanwhile, younger institutions are believed to gain benefit from previous practices and experience built-up from more established peers, or in other words, they are expected to "leapfrog older institutions" in terms of rapid learning and improvement.

Past studies thus provide mixed result about the change in efficiency as a MFI ages. In the first circumstance, the relationship is positive, whereas in the second, it is negative. In this study, I expect that MFIs operating in field have superior insights and advanced know-how practices in dealing with uncertainty typical to microfinance business. Accordingly, I hypothesize:

H3. There is positive relation between technical efficiency and institutional years of experience.

III. Research methodology

3.1 Stochastic production frontier analysis

This research employs stochastic frontier parametric-approach to measure the production frontier. Two approaches that are common in banking research are non-parametric approach and parametric approach. The former does not take a specific functional form in measuring efficiency frontier, nor is there any explicit assumption about distributional form for the error term (Worthington, 1999). One of programming techniques that has been widely used is Data Envelopment Analysis (DEA) (Charnes, et al., 2013; Seiford, 1996; Banker, et al., 1984). This technique measures the efficiency through the observation's deviation from the best-practice frontier, which formed as the piecewise linear combinations of input units that no further output unit is made given inputs (output-oriented) or no less input unit is used given output (input-oriented) (Berger & Humphrey , 1997). An advantage of DEA is the flexible structure of the frontier to allow for the incorporation of variable returns to scale. The major disadvantage is the non-measurement-error assumption, which induces the inability in dealing with irregularities in data (Worthington, 1999). This could pose a limitation in interpreting the causes of inefficiency among observations, especially when the main drivers of inefficiency are luck, data problems or selected accounting methods. Moreover, DEA does not consider the prices of inputs, which causes inability to compare between institutions that specialise in different inputs and outputs (Berger & Humphrey, 1997; Berger & Mester, 1997).

The parametric approach has been increasingly popular for its advantage of incorporating random error. The most common technique is the stochastic frontier analysis (SFA). Other alternative approaches are Distribution – Free approach (DFA) and Thick Frontier approach (TFA). These three methods differ fundamentally in the assumption regarding the distributions of the inefficiency term and random error (Berger & Humphrey , 1997). For example, DFA has no specific distributional assumption on the residuals, and it does not the separate inefficiency effect from random error (Kumbhakar, et al., 2015); TFA also imposes no assumption regarding distributions of both the composed error and inefficiency, but rather assumes random error to exist within the performance of the highest and lowest quartiles of observations compared to their predicted values, while inefficiency effect pertains between two groups (Berger & Humphrey , 1997). This study uses the SFA approach. In SFA, the components of the stochastic error term are traditional random noise with a zero mean, assumed to follow a symmetric distribution, and a strictly non-negative inefficiency measure with a nonzero mean, assumed to follow an asymmetric distribution. SFA also has the ability to address measurement errors and accounting irregularities that are normally found in analysing data in emerging countries, the feature that DFA and TFA do not hold (Servin, et al., 2012; Paxton, 2007).

The general model of output-oriented production function upon which SFA is applied implies the operational objective of output maximization given inputs. Coelli et al. (2005) propose a single-output multiple-inputs model as follows:

$$(1)\ \ y = f(x) + \varepsilon$$

In this model, y is output; $x = (x_1, x_2, \ldots, x_N)'$ is an N x 1 vector of inputs; ε is the error term. In determining the algebraic form of $f(x)$, past research identifies several common functional forms: non-flexible form – Cobb-Douglas specification, semi-flexible form – translog model, and fully flexible form -

Fourier specification (Bikker & Bos, 2008). Several characteristics that need to be considered when selecting between different forms are flexibility, linearity in the parameters, economic regularity and model parsimony (Coelli, et al., 2005). The translog function suggested by (Battese & Coelli, 1995) is estimated for data in this study for its advanced properties, including the relaxation of the Cobb–Douglas assumption of unitary elasticity of substitution; the inclusion of multiple outputs without violating curvature assumptions (Kumbhakar & Lovell, 2000); and the ability to allow technological change effects to increase or decrease over time when including a time trend in the model (Coelli, et al., 2005).

The production frontier in this study is first proposed independently by (Aigner, et al., 1977) and (Meeusen & van den Broeck, 1977), and applied by (Servin, et al., 2012). I introduce to the model an additional set of control variables capturing lending technology employed by MFIs, risk-taking behavior and country-specific factors. The model is constructed as follows:

$$(2)\ lny_{it} = \beta_0 + \sum_{j=1}^{n} \beta_j * lnx_{it}^{j} + \sum_{j=1}^{n}\sum_{k=1}^{n} \beta_{jk} * lnx_{it}^{j} * lnx_{it}^{k} + \gamma * t + \theta * t^2$$

$$+ \sum_{j=1}^{n} \alpha_j * lnx_{it}^{j} * t + \delta * control\ variables + \varepsilon_{it}$$

In this function, y_{it} denotes the production at the t-th observation for the i-th firm; x_{it}^{j} is a vector of values of known functions of input j-th of firm i-th; t represents time trend; the set of control variables includes lending methods, risk measures and regional factors; and $\varepsilon_{it}$is the error term. Parameters $\beta, \gamma, \theta, \alpha$ and δ are correlation coefficients to be estimated. Along with three input variables, the model incorporates squared form of each inputs and interaction terms between inputs. Besides, time-squared is added to allow for non-monotonic technical change, while a time trend interacted with input variables is introduced to allow for non-neutral technical change (Coelli, et al., 2005).

The regression residual ε_{it} contains two elements:

$$(3)\ \varepsilon_{it} = v_{it} - u_{it}$$

where v_{it} represents random noise – uncontrollable factors that affect production efficiency, and is assumed to be independent and identically distributed with iidN $(0; \sigma_v^2)$; u_{it} is the non-negative *technical inefficiency* variables, following Truncated-normal distribution with iidN$^+$ $(\mu_{it};\ \sigma_u^2)$(Stevenson, 1980). Regarding the distributional assumption of the later, there are other models whose application depends in part on the determination of distributional shape of the inefficiency effects (Coelli, et al., 2005). Different distributional specifications include Half-normal model with u_{it} ~ iidN$^+$ $(0;\ \sigma_u^2)$ (Aigner, et al., 1977), Exponential model with u_{it} ~ iidN$^+$ $(\eta_{it};\ \eta_u^2)$ where η is a non-negative parameter denoted to formulate the density function of u_{it}: $f(u_{it}) = {}^{1}/_{\eta_{it}} * exp({}^{-u_{it}}/_{\eta_{it}})$ (Meeusen & van den Broeck, 1977), and Gamma model with u_{it} ~ iidG (Θ_{it}, m_u) where u_{it} is distributed with mean Θ and degrees of freedom m (Greene, 1990). Kumbhakar et al. (2015) point out that the Half-normal and the Exponential models restrict the observations to cluster near full efficiency. The Gamma and the Truncated-normal models, on the other hand, imply a wider range of the distributional shape (non-zero modes), hence allow researchers

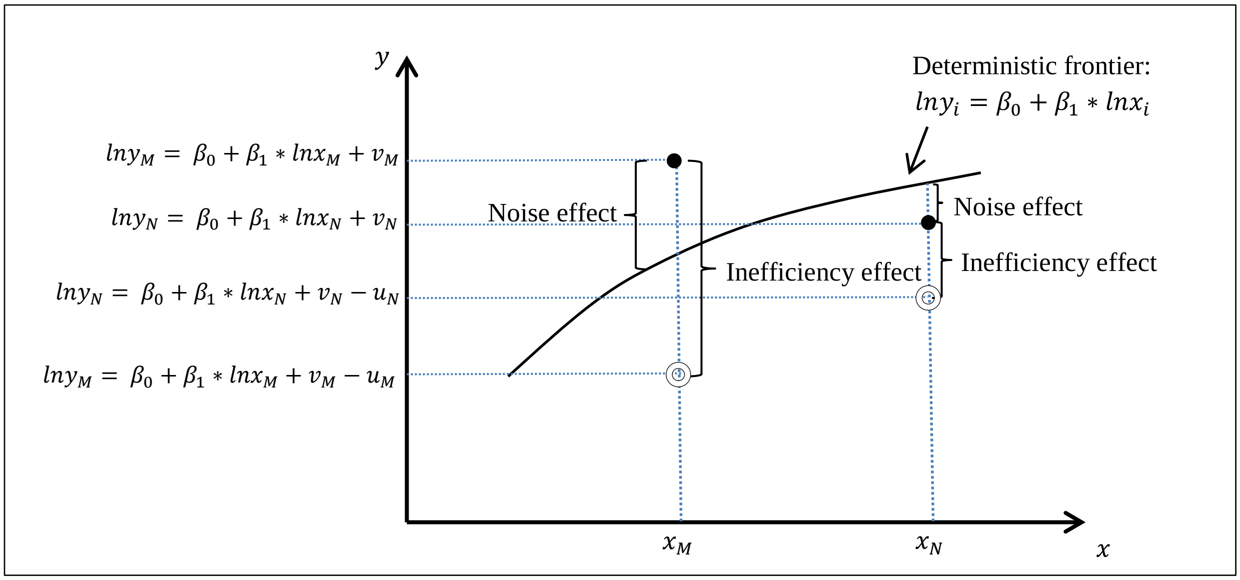

Figure 3.1: The stochastic production frontier. Source: Coelli et al. (2005)

to investigate the inefficiency with a certain degree of flexibility. The choice of Truncated-normal model over the Gamma model in this study is made for the reason of computational convenience.

A simple version of the frontier (2) with its two-component error term is illustrated graphically in Figure 3.1. Two firms M and N use inputs x_M and x_N to produce output y_M and y_N, respectively. The best production frontier for both firms is $lny_i = \beta_0 + \beta_1 * lnx_i$, in which there is neither inefficiency effect nor external noise. In the case of firm M, the frontier value (marked with a dark plot) is above the deterministic part because of its positive noise effect ($v_M > 0$), the observed output (marked with double circles) lies below the deterministic part because of the negative effect of the sum of inefficiency and external noise ($v_M - u_M < 0$; $v_M < u_M$) . Firm N, on the other hand, has negative effects both from external factors ($v_N < 0$) and from inefficiency u_N. It thus has frontier value and observed output plotted below the deterministic frontier.

The *technical efficiency* of the i-th firm at time t is defined as:

$$(4) TE_{it} = \exp(-u_{it})$$

The negative sign $(-u_{it})$ implies that inefficient institutions operate below the efficient production frontier (Bikker & Bos, 2008). TE_{it} has value between 0 and 1, where 1 implies a full efficiency level. Since the log-likelihood function of a stochastic frontier is highly nonlinear and thus imposes difficulty in estimation, a skewness test on the residuals suggested by (Kumbhakar, et al., 2015) is employed to check for the validity of the stochastic frontier specification prior to applying more complicated estimations. The logic is that the composed error term ε_{it} in the production function should be negative skewed due to v_{it} following symmetric distribution around zero while u_{it} being non-negative. Details of the basic model for this test as well as results are shown in the Appendix. In sum, the test confirms the validity of the production frontier specification.

3.2 Firm-specific determinants of technical efficiency

The four key institutional variables employed to assess the influence in the level of technical efficiency is composed in the following model:

$$(5)\ \mu_{it} = \pi_0 + \sum_{j=1}^{n} \omega_j * Z_{it}^{j}$$

in which μ_{it} is the mean of pre-truncated inefficiency u; Z_{it}^{j} depicts exogenous variables of institutional characteristics: ownership form, two measures of client outreach – average loan balance and the percentage of female borrowers, and institutional age. This parameterization approach is proposed by Battese & Coelli (1995) in an attempt to make the distributional shape of u more flexible by relaxing the constant-mean assumption of μ_{it}. More importantly, this model introduces time-varying components along with individual-specific components to allow technical efficiency to change over time and across observations.

Equation (2) and (3) are estimated simultaneously in one-step procedure by using maximum likelihood. Initially, a two-step approach was employed: the stochastic frontier was estimated in the first step with dependent variable is output y as a function of input x, plus a random error v and minus one-sided inefficiency u; then in the second step, the relationship between u and a set of exogenous factors Z is obtained through regressing u on Z. Wang & Schmidt (2002) show that two-step procedure suffers serious bias caused by unsettle assumption regarding the distribution of the inefficiency term u between two steps. Precisely, u is assumed to be independent and identically half-normally distributed in the first step, but in the second step it is assumed to be normally distributed and dependent on Z. The second problem with the two-step method is that if Z can affect output level y and Z correlates with input x, then the first-step regression without Z would yield biased results due to omitted variables. Third, even if Z and x has no correlation, there is another under-dispersed bias in estimating inefficiency u due to ignoring the dependence of the variance σ_u^2 on factors Z. To put it simple, suppose that the results from the first-step are unbiased. The residual ε is hence unbiased. When calculating the inefficiency estimate u, a "shrinkage estimator" is obtained: $u^* = E(u|\varepsilon = e)$ (Battese & Coelli, 1988). The shrinkage moves toward the mean (Wang & Schmidt, 2002). In the truncated distribution model, the mean of u^* is derived as:

$$(6)\mu^* = \frac{\sigma_v^2 * \mu - \sigma_u^2 * \varepsilon}{\sigma_v^2 + \sigma_u^2}$$

The mean μ^* from (6) is dependent of the variance σ_u^2 (Kumbhakar, et al., 2015). Since in the equation (5) the mean μ is dependent on Z, now both the mean and the variance of u depend on Z. In the second-step, large Z will translate to large u^* and also large σ_u^2. This means when shrinking u^* toward the mean, the value should be toward observations with small-u more and large- u less. Ignoring large σ_v^2 will cause the value to naturally shrink toward observations with small-u less and large-u more. Therefore, the estimation of u will be under-dispersed if the effects of Z on σ_v^2 are not taken into account.

Wang & Schmidt (2002) propose that one-step estimator shows better performance under Monte Carlo simulations test due to its correctly specified model: imposing relationship between exogenous firm characteristics Z and inefficiency u directly into estimating firm's production frontier. The correlation coefficients of input x, the efficiency level u and the coefficients of Z can be estimated by a single step, thereby mitigating some of the above methodology issues. The paper thus gives strong support for the one-step model to avoid downward biased results that are inherent in two-step model. In one-step regression, coefficients of input x in production function and of factors Z in inefficiency function, as well as all other parameters in the model, are delivered through numerical maximization procedures, i.e. a maximum likelihood method.

IV. Data and Descriptive Statistics

4.1 Data

The dataset in this research is obtained from the MixMarket™ (www.themix.org), a global non-profit organization that offers a web-based platform for MFIs to voluntarily submit their reports on operating performance. The MixMarket™ also plays a role in academic research by providing an extensive database where researchers and practitioners can assess microfinance information related to financial and social performance, classify and rate MFIs according to pre-specified performance indicators. The source provides adequate information systems and performs comprehensive checks on the accuracy and consistency of the data reported. Therefore, the MixMarket database is perceived as highly representative of the best MFIs worldwide, although certainly not for the whole population of MFIs (Gonzalez, 2007). After adjustment for missing data, the full sample consists of 3,763 observations. The number of MFIs in the study is 1,394, covering in six regions: Africa (AFRICA), East Asia & Pacific (EA&P), Eastern Europe and Central Asia (EE&CA), Latin America and Caribbean (LA&C), Middle East & North Africa (MENA), and South Asia (SA). The sample set includes 465 NGOs; 213 COOPs; 542 NBFIs; 131 Banks and 43 Rural Banks. There is no single institution that had ownership transformed during the period under estimation. The dataset has a panel structure, ranging over the period from 2010 to 2015.

The data sample in this study may not represent the whole microfinance industry partly because of the voluntary contribution to the platform. Many MFIs who target financial sustainability are more likely to submit their data, partly to improve their operational transparency and partly to inform donors and investors about their financial performance (Bauchet & Morduch, 2010). Those institutions are willing to report because they consider themselves to perform better and be more transparent within the market. Having good performance recorded gives them some benefits, such as a better access to funding. Therefore, self-reporting bias cannot be prevented. Additionally, collecting and measuring social data are often challenging, pushing MFIs to report only selected database. From the total sample collected, many MFIs did not provide full information for the entire period, and some even reported only few indicators. Removing those MFIs for the lack of data may limit the reliability and applicability of the results. The last concern regarding the dataset is that the proportion of larger institutions with higher concentration on financial objective and profitability, especially microfinance banks, may dominate the total sample. This issue is previously mentioned in several papers such as Galema, et al. (2012) and Cull, et al. (2009).

4.2 Selection of outputs and inputs

Research in the banking sector still holds an ongoing debate over the specification of inputs and outputs of bank production (Bikker & Bos, 2008). Two mainstreams that have been recognized are the production approach and the intermediation approach (Sealey & Lindley, 1977). The fundamental difference between these approaches is the classification of deposits: the former regards banks as producers of loans and deposits, whereas the latter assumes that banks act as intermediaries between depositors and borrowers, using inputs of deposits, labor and material to provide loans and investments. Several papers employing intermediation approach in microfinance industry include Abdulai & Tewari (2016), Hermes, et al. (2011), Paxton (2007) and Gregoire & Tuya (2006).

This research, however, takes the production approach as in line with Servin, et al. (2012), Gutiérrez-Nieto

Table 4.1: Definition of inputs and output of MFIs

Variable	Definition
1. Outputs – Dependent variables	
NoL	The number of loan accounts that have outstanding loan balance or have any portion of the loan portfolio. The variable is measured in thousands of account.
BORROWERS	The number of individuals or institutional clients who have an outstanding loan balance with the MFI or are bearing responsibility for repayment of any portion of the loan portfolio. The variable is measured in thousands of people.
2. Inputs – Main independent variables	
ASSETS	Asset variable measures the total size of capital that a MFI requires to purse its goal. The variable is measured in millions of US dollar.
PERSONNEL	The total number of staff members employed by MFIs. The labor forces consists of permanent staffs as well as contract advisors and managers who are not involved in the institution's roster of employees. It is measured in persons.
OPEX	The total costs including employee expenses, administrative expenses and non-cash expenses. The variable is measured in millions of US dollar.

Source: The MixMarket taxonomy (https://www.themix.org/resource/glossary/glossary)

et al. (2009) and Balkenhol (2007). Because many MFIs do not take deposits, the production approach seems appropriate for bank branches with limited autonomy in credit policy (Bikker and Bos, 2008). A more complicated issue is that the choice of outputs and inputs is a crucial part in modeling production functions since it identifies the MFIs' target of maximizing specific output quantities given inputs, hence affects the estimated level of efficiency (Hartarska, et al., 2006). In this study, a MFI is recognized as a producer of loans and credit services. The MFI is expected to provide maximum number of loan accounts (NoL) by using three sources: assets (ASSETS), staffs (PERSONNEL) and operating expenses (OPEX). For robustness check, I use as another output variable the total number of active borrowers (BORROWERS). The reason is that a single client may hold multiple loans with a MFI. Maximizing outputs in terms of the number of credit clients also conforms to the goal of an institution – to increase its client outreach. A detailed description of each of variables is shown in Table 4.1.

4.3 Control variables

Lending methodology

Hermes, et al. (2011) indicate that group-based lending influences cost function. This lending property helps reduce information costs through peer pressure, decrease associated screening, monitoring, and contract enforcement costs (Caudill, et al., 2009). The economics of joint liability group lending has earned significant interest and its effects have been clearly indicated by Hermes & Lensink (2007). Beside improving screening, monitoring and enforcement activities, group-based borrowers also have social ties that solves moral hazard (Hermes, et al., 2005); and especially for those groups having limited alternative sources of fund, they tend to enforce greater repayment pressure to members within group in order to gain future access to credit (Sharma & Zeller, 1997). One notice from previous research, however, is that group-based lending may crow out the core poor because of low repayment possibility and thus high credit risk (Marr, 2004).

While joint liability group lending offers some benefits to MFIs, individual lending, on the other hand, is perceived as bringing higher profitability on average (Cull, et al., 2007). Higher interest rate associated with individual-based lending reveals MFIs' target to seek for financial self-sufficiency through reducing operating cost per dollar lent. Besides, Cull, et al. (2007) also suggests that some cultural and social factors typical in each region may have some influence on the MFIs' preference of one lending type over another. Summary statistics in terms of lending method across regions shown in the Table A1 in the Appendix indicate that lending to individuals predominates in Eastern Europe and Central Asia, while group lending is more common in South Asia. Other regions has no particular preference in either lending style.

Since different types of lending are favoured in different countries and have different effects on MFIs' operation, it is important to include different lending methods in the production frontier model. The variables INDIVIDUAL takes the value of 1 if a MFI provides loan mainly in individual method and 0 other wise; GROUP variable represents the case of group type; VILLAGE variable takes the form of village loan; and ALL variable equals 1 if a MFI reports all three types. The last category is chosen as the reference group in the regression equation. Those MFIs that did not report any particular lending method were left out for missing data.

Risk-taking behavior

As suggested by Bikker & Bos (2008), I introduce to the model two risk indicators in order to capture the effects of risk management among MFIs. Particularly, I employ the ratio of equity over total assets (EQUITY) and loan loss rate (LLR) – measured as the value of write-off loans recovered over total loan portfolio. These variables have been widely used in microfinance literature as measures of the differences in the risk-taking strategies among MFIs (Hermes, et al., 2011; Lensink, et al., 2008; Grigorian & Manole, 2006). The ratio of equity over total assets reflects how well an institution manage its leverage: providing more loans, especially risky part, means the institution needs to obtain more capital. Hence, better capitalization, reflected in higher EQUITY ratio, is expected for maximizing number of loan outstanding. Loan loss rate, on the other hand, captures information about loan quality. More risky loans offered indicates that loan quality might be negatively affected, hence a negative correlation is expected.

Country factors

I add to the production frontier regional variables to control for geographical difference in regulation and competition. They are dummy variables; each takes the value of 1 if a MFI is located in the corresponding region that the variable represents: Africa (AFRICA); East Asia and Pacific (EA&P); Middle East and North Africa (MENA); Eastern Europe and Central Asia (EE&CA); and South Asia (SA). The last group is selected as the reference group in the regression equation.

Besides, in line with (Iannotta, et al., 2007) and (Mersland & Strøm, 2010), I employ per capita GDP at purchasing power parity (GDP), measured by current international dollar, to control for the influence of economic cycles within local markets, and to make performance and efficiency of MFIs more comparable across regions. This economic index is obtained from the World Bank (www.worldbank.org).

4.4 Firm-specific determinants of technical efficiency

Explanatory variables that characterize MFIs' technical efficiency are average loan size, the percentage of female borrowers, ownership form and institutional age. A detailed description and construction of all

Table 4.2 Definition of efficiency determinants

Variable	Definition
OWNERSHIP	Ownership variable represents for types of legal form. It takes the categorical form, which equals 1 for NGOs, 2 for COOPs, 3 for NBFIs, 4 for Banks and 5 for Rural Banks.
ALB	Average loan size equals total loan portfolio divided by total number of active borrowers. The variable is measured in thousands of US dollar.
WOMEN	The proportion of female borrowers in total client portfolio. The variable is measured in percent (%)
AGE	An indicator of a MFI's years of business experience, taking three categories: 1 for New group (less than 4 years), 2 for Young (from 4 to 8 years) and 3 for Mature institutions (over 8 years).

Source: The MixMarket taxonomy (https://www.themix.org/resource/glossary/glossary)

the variables are shown in Table 4.2.

OWNERSHIP variable reflects the legal form under which a MFI operates. The variable is assigned with an increasing value from 1 to 5 in accordance with the increasing level of commercialization. Different characteristics between legal structures imply different choices of objectives, client concentrations as well as strategic management. Constructing the variable with different categories helps better assessing the changes in technical efficiency when moving from lower-commercialized groups to higher groups. Average loan balance per borrower (ALB) measures the depth of client outreach. A smaller size implies a greater depth of outreach. MFIs focus on serving the unbanked community with small credits in order to maximize their outreach objective. The percentage of female borrowers (WOMEN), on the other hand, is an indicator of the breadth of outreach. A higher concentration on women exhibits higher outreach. Institutional age (AGE) represents different groups of MFIs based on their business experience. The aims are to compare the differences in technical efficiency among new entries, young institutions and established institutions, and investigate whether technical efficiency can be improved by operating in the market for a longer period of time.

All the monetary values are deflated by the price indexes using 2010 as the base year. Price indexes are available at International Monetary Fund (www.imf.org).

4.5 Descriptive statistics

Basic summary statistics of the dataset are featured in the Table 4.3. Panel A shows the variables that are included in the production frontier, while Panel B exhibits that of inefficiency model. The MFIs in the sample have an average of nearly 120,000 loan accounts, 94,000 credit clients. These institutions are relatively large in terms of size, with the mean total assets value is over $70 million and more than 500 staffs. One interesting finding from Panel A is the relatively large standard deviation in the number of loan accounts and the number of active borrowers. The high value may reflect a broad range of the output quantities offered by MFIs in the data sample. Similarly, the number of staffs between institutions greatly varies, with a minimum of 2 persons and maximum of over 25,000 persons. A small mean of loan loss rate (1.8%) may imply the MFIs' loan quality and the degree of risk they undertake. From the Panel B, a mean of 63.6% of female clients suggests that MFIs in the sample have a slightly higher concentration on lending to women. The mean average loan size per borrower is $2,200 and the average age of the sample approaches the 'Mature' group (over 8 years).

Table 4.3 Summary statistics

Panel A					
Variables	N	Mean	SD	Min	Max
NoL[a]	3,763	117.40	908.60	0.003	48,105.03
BORROWERS[a]	3,763	94.23	416.57	0.003	8,166.30
ASSETS[b]	3,763	73.27	404.20	0.02	19,194.70
PERSONNEL[c]	3,763	528.06	1,506.30	2	25,420
OPEX[b]	3,763	6.84	21.61	0.001	413.86
EQUITY[b]	3,763	13.72	52.0	0.29	1,355.76
LLR[d]	3,763	1.80	3.79	0	64.88
Panel B					
OWNERSHIP	3,763	2.30	1.13	1	5
ALB[e]	3,763	2.20	26.55	0.005	1,571.32
WOMEN[d]	3,763	63.60	29.10	0	100
AGE	3,665	2.66	0.63	1	3

[a] Thousands

[b] Millions of US$

[c] Persons

[d] Percent

[e] Thousands of US$

A better insight into the features of the dataset can be gained from the Table A2, A3 and A4 in the Appendix. The number of MFIs having data in a particular year is shown in the Table A2. A decreasing trend can be observed as the number of reported MFIs fell from 820 in 2010 to 456 in 2015, implying a drop of nearly 50%. Table A3 exhibits the number of year observations per MFI. Over 54% of the total MFIs have only 1 and 2 observations. The number of MFIs reporting data more than one year to The MixMarket reduces as the year observations increased. There are only 90 institutions that have data for the full 6 years. The results in Table A4 indicate that the sample is fairly balance across regions: the number of MFIs in LA&C makes up more than 30% of total sample; MFIs in EE&CA and SA contribute 19% each on average and EA&P group shares 13%. The only exception is the group in MENA, which accounts for only 3%. It is possible that a number of institutions in this region were left out for the reason of insufficient data in each observation. The data in this Table exhibits a downward trend in the number of distinct MFIs having data reported to The MixMarket from 2010 to 2015 in all regions. In sum, the total sample in this study is relatively larger than that of past research, and the portion of different regions is somewhat comparable, suggesting an improvement the accuracy when examining the overall trend in the whole microfinance industry.

V. Empirical Results

5.1 Main findings

Table 5.1 presents the results of econometric estimations. I performed six separate regression models that simultaneously estimate the production frontiers and their associated inefficiency equations. Model (1) is the base model for the production function with inefficiency u_{it} estimated under the assumption of constant-mean condition. Model (2) includes ALB and model (3) replaces ALB with WOMEN in total borrowers to investigate whether "mission drift" exists. Model (4) adds both measures to test for the overall outreach effects at both the depth and the breadth dimensions. Model (5) serves as the full model which inefficiency level is examined against four explanatory variables: ALB, WOMEN, OWNERSHIP and AGE. Panel A reports the estimation results of production frontier equations, while panel B exhibits the results of the inefficiency functions with different firm-characteristic determinants.

Parameters estimated from the base model (1) produce some noteworthy findings. Firstly, the coefficient of the constant (μ_{it}) in the inefficiency equation is significant, supporting the appropriateness of truncated-normal distributional assumption of the inefficiency term u_{it} against the hypothesis of half-normal distribution (H0: μ = 0). Secondly, the one-sided test concerning the existence of inefficiency term as suggested by Coelli (1995) produces *z*-value of 12.000 (p-value = 0.000), thus the null hypothesis of no inefficiency in the sample is reasonably rejected. Finally, z-test with regard to the time-invariant efficiency effects (H0: η = 0) produces z-value of -3.14 (p-value = 0.000). The associated null hypothesis of no technical change effects is rejected, suggesting that the model contains a certain level of output improvement resulting from technological progress over time (Coelli, et al., 2005).

The coefficient of time trend variable in the based model (1) is 0.092, indicating unconditional mean technical progress of 9.2% per year. The time-squared variable is positive and statistically significant at 10%, showing that the rate of technical change rises at an increasing rate through time. The coefficient of the interaction term between time trend and personnel is positive and significant, while that of time trend and operating cost is negative and significant. These results show that technical change in MFIs has been labor-augmenting and cost-saving. MFIs in the sample tend to invest in staff training and emphasize cost effectiveness in operation. The sum of the coefficients of the three input variables in model (1) equals 1.12, implying an increasing return to scale. Such a potential growth in output among MFIs can be found also in Servin, et al. (2012) (unreported) and Hartarska, et al. (2006).

From the panel A, the sign of all three inputs, ASSETS, PERSONNEL and OPEX, are consistent across models, but the significance is varying. While the coefficient of PERSONNEL is positive and statistically significant in all six models, the coefficient of ASSETS becomes insignificant in the full model (5). A possible explanation is due to potential correlation between ASSETS and AGE variable in the inefficiency equation: the MFI's assets grow as it stays for more years in field. Results of pairwise correlations presented in Table A5 in the Appendix confirm such positive relation. OPEX become more important in the model (5) because MFIs cannot neglect financial self-sufficiency if they desire for a long-term expansion. Additional control variables, LLR, regional dummies, GDP and lending dummies are generally consistent in sign and significance across specifications.

Table 5.1 Production frontier and inefficiency estimates

Panel A: Frontier estimates	(1)	(2)	(3)	(4)	(5)
Ln(ASSETS)	0.416***	0.424***	0.483***	0.404***	0.052
	(0.080)	(0.094)	(0.090)	(0.089)	(0.085)
Ln(PERSONNEL)	0.551***	0.513***	0.463***	0.524***	0.787***
	(0.064)	(0.070)	(0.068)	(0.068)	(0.063)
Ln(OPEX)	0.151**	0.123	0.067	0.103	0.192***
	(0.059)	(0.075)	(0.073)	(0.071)	(0.068)
Ln(ASSETS)*Ln(ASSETS)	-0.024**	-0.022*	-0.032***	-0.012	0.042***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.010)
Ln(PERSONNEL)*Ln(PERSONNEL)	0.059***	0.022*	0.032***	0.031***	0.031***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.010)
Ln(OPEX)*Ln(OPEX)	0.015***	-0.0003	0.012*	0.008	0.005
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Ln(ASSETS)*Ln(PERSONNEL)	0.014	0.012	0.029*	-0.0006	-0.079***
	(0.015)	(0.017)	(0.017)	(0.017)	(0.016)
Ln(PERSONNEL)*Ln(OPEX)	-0.084***	-0.023	-0.067***	-0.036*	0.022
	(0.018)	(0.021)	(0.020)	(0.020)	(0.019)
Ln(ASSETS)*Ln(OPEX)	0.021**	0.017	0.032***	0.016	-0.017
	(0.010)	(0.013)	(0.012)	(0.012)	(0.011)
Ln(ASSETS)*YEAR	-0.001	-0.002	-0.007	-0.007	0.006
	(0.005)	(0.009)	(0.009)	(0.009)	(0.008)
Ln(PERSONNEL)*YEAR	0.021***	0.039***	0.037***	0.036***	0.021***
	(0.004)	(0.008)	(0.008)	(0.007)	(0.007)
Ln(OPEX)*YEAR	-0.022***	-0.039***	-0.034***	-0.033***	-0.030***
	(0.006)	(0.010)	(0.010)	(0.010)	(0.009)
YEAR	0.092***	0.053	0.089*	0.086*	0.003
	(0.026)	(0.048)	(0.046)	(0.045)	(0.042)
YEAR*YEAR	0.004*	0.008*	0.006	0.006	0.008**
	(0.002)	(0.005)	(0.005)	(0.005)	(0.004)
EQUITY	0.028	0.020	0.001	0.025	0.067
	(0.041)	(0.050)	(0.048)	(0.048)	(0.045)
LLR	-0.194	-1.177***	-1.015***	-0.999***	-1.045***
	(0.202)	(0.326)	(0.315)	(0.309)	(0.286)
AFRICA	-0.838***	-0.703***	-0.523***	-0.536***	-0.614***
	(0.080)	(0.054)	(0.053)	(0.052)	(0.048)
EA&P	-0.747***	-0.565***	-0.555***	-0.548***	-0.556***
	(0.081)	(0.047)	(0.046)	(0.045)	(0.043)
EE&CA	-1.400***	-1.124***	-0.885***	-0.908***	-0.971***
	(0.086)	(0.052)	(0.052)	(0.051)	(0.048)
LA&C	-0.835***	-0.618***	-0.517***	-0.539***	-0.749***
	(0.080)	(0.053)	(0.051)	(0.050)	(0.047)
MENA	-0.535***	-0.372***	-0.174**	-0.202***	-0.484***
	(0.133)	(0.075)	(0.073)	(0.072)	(0.068)
GDP	-0.013***	-0.008***	-0.013***	-0.012***	-0.006**
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
INDIVIDUAL	-0.222***	-0.520***	-0.367***	-0.371***	-0.338***
	(0.043)	(0.046)	(0.045)	(0.044)	(0.041)
GROUP	0.005	0.072	0.044	0.038	0.062
	(0.043)	(0.050)	(0.048)	(0.047)	(0.043)
VILLAGE	0.007	0.196***	0.117*	0.111*	0.121**
	(0.048)	(0.062)	(0.060)	(0.059)	(0.054)
Constant	4.735***	-3.063	-3.022	-2.964	-2.133
	(0.898)	(16.71)	(10.63)	(24.11)	(38.77)

Panel B: Inefficiency estimates with the mean of conditional distribution of u_{it}					
ALB		0.005***		0.005***	0.051***
		(0.0004)		(0.0004)	(0.003)
WOMEN			-1.052***	-1.033***	-0.832***
			(0.052)	(0.051)	(0.048)
OWNERSHIP					0.102***
					(0.011)
AGE					-0.081***
					(0.018)
Constant	8.238***	0.170	1.206	1.181	1.205
	(0.857)	(16.71)	(10.63)	(24.11)	(38.77)
γ	0.888	0.002	0.002	0.002	0.005
	(0.006)	(0.389)	(0.266)	(0.538)	(1.401)
σ_u^2	0.612	0.001	0.0009	0.0008	0.002
	(0.026)	(0.192)	(0.122)	(0.238)	(0.520)
σ_v^2	0.077	0.491	0.458	0.442	0.369
	(0.002)	(0.192)	(0.122)	(0.238)	(0.520)
Observations	3,757	3,757	3,757	3,757	3,659
Wald $\chi^2(25)$	10278	28464	28889	29865	29572
Log likelihood	-2560	-3998	-3867	-3801	-3378

Note: Dependent variable in all six models is log (NoL);
Standard errors are in parentheses; *** indicates statistical significance at the $\alpha = 1\%$, ** at the $\alpha = 5\%$ and * at the $\alpha = 10\%$.
Detailed parameters from the base model (1): σ_u=0.782; σ_v=0.278; σ^2=0.689; eta (η) = -0.005***; lambda (λ) = 2.813.

Results in Panel B depict firm-specific factors that cause inefficiency variation. The coefficients of ALB are positive and significant in model (2), (4) and (5). That means lowering average loan balance helps reduce inefficiency, or in other words, increase technical efficiency. The WOMEN variable has negative and significant coefficients in model (3), (4) and (5), implying that higher share of female clients in the total number of borrowers boosts technical efficiency. The two hypotheses 1a and 1b can thus be confirmed. While the negative correlation between WOMEN and the inefficiency is similar to that of Abdulai & Tewari (2016), Kumar & Sensarma (2015) and Hartarska, et al. (2006), interpreting the positive relationship between ALB and the inefficiency should be carried with caution. Past studies suggest that the effects of ALB is nonlinear, that is, there is a threshold in which further reduction in ALB would raise inefficiency (Kumar & Sensarma, 2015; Paxton, 2007). This may due to the fact that lending micro credits is costly for any institutions and that benefits from scale economies can only be maintained up to a certain point (Kumar & Sensarma, 2015).

The OWNERSHIP variable is positive and significant in the model (5). It means that as moving from non-shareholder group to shareholder group, the level of inefficiency increases, i.e. technical efficiency decreases. In other words, non-shareholder MFIs are more technically efficient than shareholder MFIs. The most efficient group is NGOs, followed by COOPs and NBFIs. The least efficient group is Banks and Rural Banks. This result confirms hypothesis 2 and is in line with Kumar & Sensarma (2015), Haq, et al. (2010), Hassan & Sanchez (2009). Possible explanations include higher concentration on social target and less pressure from regulating authorities among non-shareholder MFIs as compared to shareholder MFIs. Finally, the Age variable is negative and statistically significant, indicating that older MFIs are more efficient. The third hypothesis is hence confirmed. Such a relation is in line with Caudill, et al. (2009), Paxton (2007) and Gregoire & Tuya (2006) who find that experienced MFIs have more advanced knowledge and superior insights in field through learning by doing.

Summarizing the results in table 5.1, I find a strong empirical support for higher technical efficiency among non-shareholder and experienced MFIs with their emphasis on double missions, especially the social target that reaches more poor clients. These findings remain the expected sign and statistical significance across specifications. Additionally, the results indicate that there is apparently a lack of mission drift in the data set, as similar to that of Mersland & Strøm (2010).

5.2 Robustness check

Table A6 illustrates the estimation of the frontiers with the number of active borrowers selected as a dependent variable. The correlation coefficients of the three inputs in the frontiers displayed in the Panel A remain their signs and significance as in the main frontier where the number of loan outstanding is the dependent variable. The YEAR and YEAR-squared variables confirm the effects of technological improvement over time. The interaction terms between inputs and time support the finding that those institutions in the sample tend to focus on staff straining while reducing cost in order to enhance the efficiency level.

From the Panel B, the correlation coefficients of ALB, WOMEN, OWNERSHIP and AGE are consistent in expected sign and significance, although with higher in magnitude. Improving client outreach by lowering average loan balance and targeting more women is associated with higher technical efficiency. Non-shareholder and older MFIs are more technically efficient. The results thus remain robust when it comes to a different output variable.

The only exception with the variable ALB is presented in the model (2). In this case, its positive influence is insignificant even at 10% confidence interval. A possible explanation is that since an institution is now assumed to choose a production plan that maximizes the number of borrowers, it has less incentives to reduce further average loan balance. Because lending more loans in small volume is associated with high transaction costs and high risks, MFIs may give higher attention on targeting women for their higher repayment rate. D'espallier & Mersland (2011) note that higher proportion of women in the client portfolio is linked with lower portfolio risk and reduced write-off rates. Hence, MFIs are more likely to enter lending contracts with female clients for better repayment performance while maintaining output maximization target.

VI. Concluding Remarks

This study investigates the effects of firm-specific characteristics on technical efficiency among MFIs by using stochastic frontier analysis under production approach. Empirical tests on 1,394 institutions across six regions show that technical efficiency can be gained actively from reducing average loan balance, expanding loans to more poor women, and learning by doing. Additionally, the tests yield strong favor over non-shareholder MFIs: NGOs are apparently more efficient than Banks and Rural Banks under production approach. The intermediate groups are COOPs and NBFIs, respectively. NGOs and COOPs groups perform better for a higher priority given to social goal and less burden from banking authorities as compared to NBFIs, Banks and Rural Banks. The study also indicates no existence of efficiency-outreach trade-off, hence encouraging non-shareholder NGOs and COOPs to strive for greater client outreach.

From the estimation of the production frontier under different specifications, regional dummies and GDP variable are statistically significant at 1% confidence interval. The results reveal that there are significant differences in efficiencies across border, coming from regional factors such as economic conditions, regulation, politics and culture. This implies that MFIs operate efficiently in their home country might not maintain comparable level if moving to another region. Microfinance researchers and practitioners may need to take into account the influence of environmental features when assessing technical efficiency between MFIs in different areas. Besides, LR-tests after frontier for the base model (1) and for specific regions rejects the null hypothesis of the existence of a single production frontier that applies for all regions. It is possible that such local environment has some influential power over the shape and position of the frontiers of MFIs between areas at first, apart from the different efficiency levels. Therefore, it would be interesting to look for some potential differences that might arise when applying the results from this study in specific cases.

The most important limitation in this study is that the models used do not take into account the effects of subsidy. Operation of NGOs and COOPs is heavily depends on subsidies, which may boost their efficiency to a higher level than NBFIs, Banks and Rural Banks. Caudill, et al. (2009) argue that having subsidized limits MFIs' incentives to pursue cost efficiency. Hence, it could be that subsidies keep cost-inefficient MFIs alive, even though they are technically efficient, i.e. they may weigh social target over financial target. Past research using cost frontier and estimating cost efficiencies among MFIs in fact has confirm that in terms of cost-minimization motive, non-shareholder MFIs are less efficient and that there is existence of "mission drift" (for example, Hermes, et al., 2011). Hudon & Traca (2011) investigate the relationship between subsidies and efficiency by using data from independent microfinance rating agencies. They find positive correlation, yet it is nonlinear: over-subsidization may lead to counter effects. Therefore, further research is needed to search for potential effects of subsidies variable on technical efficiency estimates among MFIs.

Regarding the importance of the choices of outputs and inputs, future research could look beyond the quantities of loan products and introduce other credit services offered by MFIs such as the number of saving accounts, insurance services and other financial advices. Because the methodology for the selection of one output over another has not yet made available, efficiency estimates from the case of single-output may be limited to certain application (Zang & Garvey, 2008). To deal with multiple outputs, a stochastic distance functions as initially suggested by (Fare, et al., 1993) and applied by (Coelli & Perelman, 2000) can be construct to account for the multi-output nature and the associated technical efficiency.

Another way to extend this study is to improve the quality of the dataset by exploring data from different sources. Existing papers have been using MFIs information from independent credit rating agencies, such as MicroRate, Microfinanza and Planet Rating. These agencies collect and analyze data, then issue risk assessment reports that are approved by C-GAP Ratingfund, hence can partly reduce the bias toward large microfinance banks existing in dataset from the MixMarket (Mersland & Strøm, 2009; Galema, et al., 2012). Moreover, some additional information regarding governance arrangements and funding structure obtained from these sources may offer insights into the way MFIs is characterized with different internal governance, choices of capital structure and how they can be translated to different efficiencies.

Finally, Berger & Humphrey (1997) demonstrate that nonparametric and parametric approaches have their own benefits and drawback. The paper suggests that studies that are interested in measuring firm-level efficiency should reexamine the findings by applying more than one frontier technique to the same dataset to verify the robustness of the explanatory results. Hence, future studies could apply other econometric approaches, such as DEA, DFA and TFA, to check for the validity of the results and any possible differences that can be emerged between these methods.

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APPENDIX

Table A1: MFI lending method by Region

	Total	AFRICA	EA&P	EE&CA	LA&C	MENA	SA
	1580	241	200	287	481	55	316
INDIVIDUAL	*863*	124	104	230	281	32	92
GROUP	*482*	84	83	47	78	21	169
VILLAGE	*114*	9	6	2	50	1	46
ALL	*121*	24	7	8	72	1	9

Table A2: The number of MFIs in a given year

Fiscal Year	Total observations in the Year
2010	820
2011	801
2012	576
2013	548
2014	562
2015	456

Table A3: The number of year observations per MFIs

Number of year observations available	Number of MFIs
1	431
2	329
3	209
4	168
5	167
6	90

Table A4: Number of MFIs per year across regions

	Total	Region					
Fiscal Year		AFRICA	EA&P	EE&CA	LA&C	MENA	SA
Number of distinct MFIs	*1,394*	215	179	264	428	48	260
2010	*375*	59	43	90	112	18	53
2011	*308*	52	60	43	92	10	51
2012	*188*	40	12	41	54	3	38
2013	*164*	16	9	29	69	3	38
2014	*184*	20	30	31	55	6	42
2015	*175*	28	25	30	46	8	38

Table A5 Pairwise correlation

	NoL	BORR	ASSETS	PERS	OPEX	YEAR	EQ	LLR	AF	EA&P	EE&CA	LA&C	MENA	SA	IND	GR	VIL	ALL	ALB	W	OWNERS	AGE
NoL	1.00																					
BORR	0.50	1.00																				
ASSETS	0.18	0.35	1.00																			
PERS	0.42	0.86	0.37	1.00																		
OPEX	0.23	0.45	0.50	0.61	1.00																	
YEAR	0.01	0.03	-0.01	0.04	0.02	1.00																
EQ	-0.05	-0.07	-0.10	-0.11	-0.13	-0.02	1.00															
LLR	0.0002	0.01	0.001	0.04	0.15	-0.05	0.07	1.00														
AF	-0.03	-0.04	-0.03	-0.04	-0.04	-0.03	0.02	0.01	1.00													
EA&P	0.002	0.01	0.04	-0.01	-0.04	0.02	-0.001	-0.09	-0.12	1.00												
EE&CA	-0.05	-0.08	-0.02	-0.07	-0.05	-0.01	0.08	-0.03	-0.15	-0.17	1.00											
LA&C	-0.05	-0.08	0.04	-0.06	0.15	-0.01	0.02	0.19	-0.25	-0.28	-0.35	1.00										
MENA	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	0.17	-0.03	-0.06	-0.07	-0.09	-0.14	1.00									
SA	0.12	0.19	-0.03	0.18	-0.08	0.04	-0.18	-0.12	-0.17	-0.19	-0.23	-0.39	-0.10	1.00								
IND	-0.03	-0.02	0.07	0.01	0.10	-0.005	-0.05	0.005	-0.01	-0.03	0.23	0.10	0.003	-0.29	1.00							
GR	0.007	0.03	-0.07	0.0003	-0.10	0.01	0.02	-0.06	0.02	0.10	-0.14	-0.27	0.05	0.32	-0.73	1.000						
VIL	0.05	-0.006	0.02	-0.01	-0.04	-0.01	0.04	0.05	-0.04	-0.07	-0.12	0.09	-0.04	0.10	-0.30	-0.17	1.00					
ALL	-0.01	-0.01	-0.02	-0.004	0.03	-0.003	0.02	0.05	0.02	-0.06	-0.09	0.20	-0.05	-0.10	-0.33	-0.19	-0.08	1.00				
ALB	-0.008	-0.01	0.04	-0.01	0.004	-0.01	0.04	-0.02	-0.02	0.06	0.02	-0.01	-0.01	-0.04	0.06	-0.04	-0.02	-0.02	1.00			
W	0.07	0.11	-0.12	0.06	-0.14	0.02	0.003	-0.04	-0.07	0.13	-0.30	-0.14	-0.05	0.41	-0.51	0.41	0.21	0.06	-0.08	1.00		
OWNERS	0.003	0.03	0.15	0.07	0.21	0.03	-0.14	0.06	0.02	0.04	0.21	-0.08	-0.13	-0.10	0.16	-0.07	-0.10	-0.09	0.04	-0.27	1.00	
AGE	0.05	0.08	0.07	0.11	0.11	0.10	-0.14	0.04	-0.11	-0.02	-0.07	0.17	0.03	-0.05	0.04	-0.09	-0.01	0.10	-0.03	-0.02	-0.20	1.00

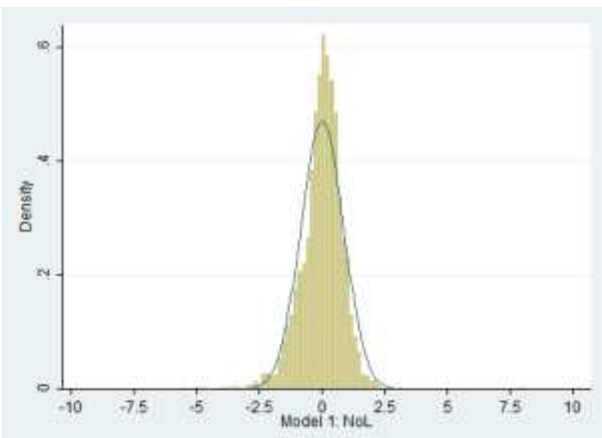
Test for the validity of the production frontier (Kumbhakar, et al., 2015):

The model used to perform OLS regression and skewness test on the residual is as follows:

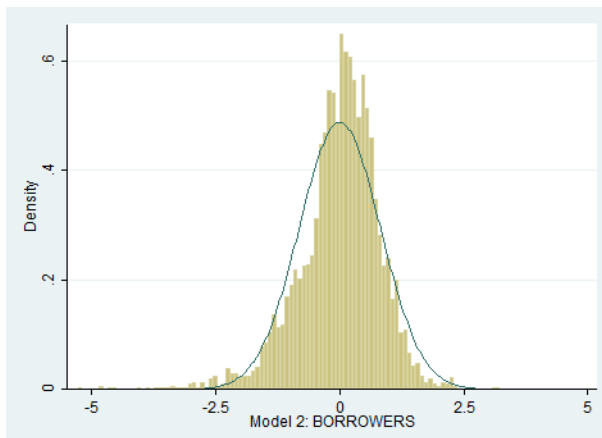
$$(3)\ lny_i = \beta_0 + \sum_{j=1}^{n} \beta_j * lnx_i^j + \varepsilon_i,$$

$$(4)\ \varepsilon_i = v_i - u_i$$

In the equation, y_i represents output of firm i-th, x_i^j is a vector of values of input j-th of firm i-th. Kumbhakar, et al. (2015) suggest that the residual ε_i, which consists of the random error v_i being symmetrically distributed around zero and the non-negative inefficiency u_i, should be negatively skewed. It is because the deviation from the best-practice production frontier of a MFI implies that its position lies under the frontier. The OLS estimation results with different dependent variables (Number of loan accounts and number of active borrowers) provide some evidence that the residuals in both cases are skewed to the left (Figure A1 and A2). The skewness tests on the residuals of the two models confirm that the negative skewness is statistically significant at 5% and 1% respectively. The null hypothesis of no skewness can be rejected. Hence, The results provide some supports for the validity of the stochastic frontier specifications.



(1)



(2)

Figure A1: Histogram of OLS residual in case the output is the number of loan accounts
Figure A2: Histogram of OLS residual in case the output is the number of active borrowers

Table A6. Frontiers and efficiency estimation – Robustness check

Panel A: Frontier estimates	(1)	(2)	(3)	(4)	(5)
Ln(ASSETS)	0.452***	0.451***	0.430***	0.402***	0.042
	(0.067)	(0.079)	(0.077)	(0.080)	(0.077)
Ln(PERSONNEL)	0.626***	0.618***	0.600***	0.600***	0.794***
	(0.053)	(0.059)	(0.056)	(0.055)	(0.056)
Ln(OPEX)	0.128***	-0.035	-0.019	0.009	0.197***
	(0.049)	(0.067)	(0.065)	(0.067)	(0.063)
Ln(ASSETS)*Ln(ASSETS)	-0.022***	-0.015	-0.010	-0.004	0.045***
	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
Ln(PERSONNEL)*Ln(PERSONNEL)	0.060***	0.029***	0.030***	0.029***	0.025***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Ln(OPEX)*Ln(OPEX)	0.015***	0.009	0.010	0.008	0.004
	(0.004)	(0.007)	(0.007)	(0.007)	(0.006)
Ln(ASSETS)*Ln(PERSONNEL)	0.002	-0.016	-0.022	-0.028**	-0.083***
	(0.012)	(0.015)	(0.014)	(0.014)	(0.014)
Ln(PERSONNEL)*Ln(OPEX)	-0.079***	-0.017	-0.018	-0.009	0.035**
	(0.015)	(0.019)	(0.018)	(0.018)	(0.017)
Ln(ASSETS)*Ln(OPEX)	0.020**	0.019	0.018	0.013	-0.023**
	(0.008)	(0.012)	(0.011)	(0.012)	(0.011)
Ln(ASSETS)*YEAR	-0.0003	-0.003	-0.006	-0.007	0.003
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)
Ln(PERSONNEL)*YEAR	0.020***	0.033***	0.036***	0.038***	0.025***
	(0.003)	(0.007)	(0.006)	(0.006)	(0.006)
Ln(OPEX)*YEAR	-0.023***	-0.032***	-0.033***	-0.033***	-0.033***
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)
YEAR	0.098***	0.043	0.069*	0.074*	0.020
	(0.022)	(0.040)	(0.038)	(0.038)	(0.037)
YEAR*YEAR	0.003*	0.009**	0.009**	0.009**	0.010***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
EQUITY	0.045	0.207***	0.224***	0.215***	0.161***
	(0.033)	(0.041)	(0.039)	(0.039)	(0.039)
LLR	-0.085	-0.911***	-0.905***	-0.865***	-0.922***
	(0.158)	(0.283)	(0.268)	(0.267)	(0.256)
AFRICA	-0.819***	-0.591***	-0.497***	-0.484***	-0.521***
	(0.076)	(0.047)	(0.047)	(0.045)	(0.042)
EA&P	-0.725***	-0.438***	-0.434***	-0.432***	-0.462***
	(0.079)	(0.040)	(0.037)	(0.036)	(0.036)
EE&CA	-1.418***	-1.186***	-1.144***	-1.132***	-1.038***
	(0.082)	(0.045)	(0.043)	(0.043)	(0.046)
LA&C	-0.810***	-0.782***	-0.803***	-0.794***	-0.822***
	(0.075)	(0.047)	(0.044)	(0.044)	(0.044)
MENA	-0.468***	-0.499***	-0.475***	-0.458***	-0.526***
	(0.128)	(0.061)	(0.059)	(0.059)	(0.059)
GDP	-0.017***	-0.006**	-0.006**	-0.006**	-0.005**
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
INDIVIDUAL	-0.171***	-0.469***	-0.401***	-0.394***	-0.355***
	(0.034)	(0.037)	(0.036)	(0.036)	(0.035)
GROUP	0.018	0.015	-0.008	-0.008	0.030
	(0.034)	(0.040)	(0.037)	(0.038)	(0.037)
VILLAGE	-0.015	0.148***	0.111**	0.106**	0.107**
	(0.038)	(0.050)	(0.045)	(0.045)	(0.045)
Constant	10.63	4.223***	4.154***	4.188***	4.736***
	(6.813)	(0.220)	(0.211)	(0.212)	(0.206)

Panel B: Inefficiency estimates with the mean of conditional distribution u_{it}					
ALB		0.068		0.006***	0.059***
		(0.102)		(0.0008)	(0.003)
WOMEN			-7.113***	-4.153***	-1.155***
			(1.581)	(0.613)	(0.085)
OWNERSHIP					0.163***
					(0.020)
AGE					-0.160***
					(0.028)
Constant	7.610	-98.79	0.30	0.984***	1.228***
	(6.823)	(165.3)	(0.451)	(0.176)	(0.10)
γ	0.928	0.997	0.949	0.914	0.704
	(0.004)	(0.005)	(0.011)	(0.013)	(0.033)
σ_u^2	0.584	52.809	2.652	1.435	0.303
	(0.025)	(87.063)	(0.653)	(0.243)	(0.032)
σ_v^2	0.045	0.169	0.142	0.134	0.128
	(0.001)	(0.009)	(0.008)	(0.008)	(0.010)
Observations	3,757	3,757	3,757	3,757	3,659
Wald $\chi^2(25)$	12443	37046	40062	40166	38271
Log likelihood	-1884	-3606	-3421	-3396	-2990

Note: Dependent variable in all six models is log (Borrower);
Standard errors are in parentheses; *** indicates statistical significance at the $\alpha = 1\%$, ** at the $\alpha = 5\%$ and * the $\alpha = 10\%$.
Detailed parameters from the base model (1): σ_u = 0.764; σ_v = 0.213; σ^2 = 0.629; eta (η) = -0.005***; lambda (λ) = 3.587.