Master thesis

Efficiency drivers in microfinance institutions

By

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The master thesis is carried out as a part of the education at University of Agder and is therefore approved as such. However, this does not imply that the University answers for the methods that are used or the conclusions that are drawn.

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ABSTRACT

This study attempts to identify drivers for efficiency in Micro Finance Institutions (MFIs) and determine their effect on the overall cost-efficiency of MFIs. The study used cross sectional data of 377 MFIs from 74 countries. Multivariate regression analysis was applied in order to find the results. Operational expense to portfolio, operational expense to assets and cost per credit client were used as efficiency measurements, 13 hypotheses were proposed and 17 variables were studied. Our results revealed that all except for two variables had a significant effect on one or more of the efficiency measurements. Credit officer productivity, cost per employee, loan outstanding average and credit officer ratio had a strong significant effect on all measurements. Our findings suggest that MFIs should increase their credit officer productivity and decrease the personnel expenses per employee in order to increase the overall cost-efficiency. Moreover, the MFIs should put more of their staff into income generating activities. Our findings also indicate that the MFIs should focus on more cost-efficient operations to avoid increased average loan amount and mission drift. Performance pay had no significant effect on the MFIs overall efficiency, which indicates that the MFIs incentive schemes motivate other performance measures than cost-efficiency. Modified incentives schemes should be considered to improve the cost-efficiency of MFIs.

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LIST OF ABBREVATIONS

CC	-	Cost per Credit client
CE	-	Cost per Employee
CGAP	-	Consultive Group to Assist the Poor
COProd	-	Credit Officer Productivity
CO	-	Credit Officer Ratio
EECA	-	Eastern Europe and Central Asia
IL	-	Individual Lending
LA	-	Latin America
LOA	-	Loan Outstanding Average
MC	-	Market Competition
MENA	-	Middle East and North Africa
MFI	-	Microfinance Institutions
MIX	-	Microfinance Information Exchange, Inc
OEA	-	Operating Expense to Assets
OEP	-	Operating Expense to Portfolio
OLS	-	Ordinary Least Squared
p.a	-	per annum
PerP	-	Performance Pay
PureFS	-	Pure Financial Service
SG	-	Solidarity Groups
UaR	-	Urban and Rural
USD	-	United States Dollar
VB	-	Village Banking
WLS	-	Weighted Least Squared

1. INTRODUCTION

1.1 MOTIVATION

As microfinance has developed from being small and narrow donor dependent activity into becoming an industry, more focus has been put on the need for efficient operations (Baumann, 2004; Hermes, Lensink, & Meesters, 2008; Qayyum, 2006). There is a proliferated knowledge about the problems of inefficiency in the microfinance industry, and many MFIs strive to increase their efficiency. However, few studies are actually testing whether the efficiency drivers, as claimed by the literature, have a significant effect on the overall efficiency of MFIs. This thesis responds to the need for more knowledge of what is affecting the MFIs overall efficiency, focusing on operational costs.

MFIs are characterized by its dual mission of serving the poor and also being financial sustainable (Begona Gutiérrez-Nieto, Serrano-Cinca, & Mar Molinero, 2007c
; Helms, 2006).They promote financial services to poor and low income people who are often ignored by commercial banks and other lending institutions, even though poor and low income people tend to have promising investments ideas than can be profitable(Gateway, 2009; Hollis & Sweetman, 1998; Ledgerwood, 1998; Robinson, 2001). This is due to the fact that poor people often have little or no collateral to back up the loan (Ledgerwood, 1998). Microcredit Summits (2007) annual report estimated that about 133 million credit clients are served worldwide and the number is increasing rapidly. Yet, only a fraction of the need is covered. It is estimated that about 3 billion people would benefit from microfinance services(Helms, 2006).

Microfinance institutions are improving the every-day life for millions of people around the world, and it has in the latest years been fronted as the “silver bullet” in the fight against poverty (Karnani, 2008) At the same time, being self-sustainable is a major challenge in the industry and many of the MFIs are depending on donors(R Mersland & Strøm, 2008a). Many argue that depending on donations is only a short-term solution and MFIs can only exist in the long run, providing beneficial financial services to the poor, if the MFIs can liberate from donors and become self-sustainable (Arsyad, 2005; Maddison, 2006). A recent study of 704 MFIs conducted by the Microbanking Bulletin (2007) reveals that 41% are not financially self-sustainable and rely on donor support. The microfinance industry is far from being “donor free”, and some might argue that it never will be. Regardless of having a donor dependent industry or not, present donors still want to know that resources are used in an efficient way. Efficient use of resources and focus on efficiency in MFIs is important to obtain self-sustainability and become independent from donors. Increased competition among MFIs is also starting to force efficiency higher up on the agenda. Additionally, commercial banks have become more interested in providing microfinance services due to the high levels of profitability among some MFIs in the recent years (Hermes, et al., 2008). Rhyne and Otero (2006) state that MFIs have to increase their efficiency in order to remain in business. Another reason to focus on efficiency can be found in Mersland and Strøm (2008a). They suggest that cost efficient MFIs are needed to avoid mission drift. Increasing profit leads to an increase in average loan size which crowds out poorer clients, leading to mission drift (Freixas & Rochet, 2008). If an MFI increases cost-efficiency more than average profit, we should not expect mission drift (R Mersland & Strøm, 2008a). Nieto et.al (2007c)find in their analyses that the majority of socially efficient MFIs are also financially efficient. In other words, MFIs focusing on social objectives should also focus on financial efficiency.

Providing small financial services involve high transaction costs in terms of screening, monitoring and administrative costs (Hulme & Mosley, 1996). MFIs seeking financial sustainable operations have to charge high interest rates to cover the extra costs providing small loan amounts (CGAP, 2009c), which are far from being competitive against interest rates in commercial banks. The average cost of credit in developing countries is still much higher than in developed countries. Yet, what is more important than being competitive, is that poor and low income people would benefit from a less expensive credit. Gonzalez (2007) reports that operational costs represent about 2/3 of charges to borrowers. Since operational costs are the largest component of interest rates, attention should be emphasized towards identifying their drivers and quantifying them in order to improve efficiency in MFIs. To demonstrate why a focus on efficiency and operational costs is important regarding the loan rate, we are presenting the loan rate R as a function of profit, deposit rate and administrative costs. Building upon Hulme and Mosley (1996, p. 19), the MFIs profit function may be written:

$$\pi = \left[(R - D) - \sum \left(Rp_j + a_j \right) \right] \sum X_j$$

where R is 1+ the loan rate; D is 1+the deposit rate, p_j is the default rate; a_j is administrative costs; and x_j is the loan number j. The last sum is the MFIs loan portfolio.

Solving for the loan rate, we find that the loan rate is a function of profit, deposit rate and administrative costs:

$$R=\frac{\pi}{\Sigma X_j(1-\Sigma p_j)}+\frac{D}{(1-\Sigma p_j)}+\frac{\Sigma a_j}{(1-\Sigma p_j)}$$

It is reasonable to assume that profit seeking will lead to mission drift, hence increased profit is not preferred on behalf of higher loan rate (R Mersland & Strøm, 2008a). We can also assume that donor free and self-sufficient MFIs have a deposit rate equal to a subsidized free market rate. The loan rate function reveals that reducing administration costs is a crucial factor for reducing loan rate. According to our loan rate function we can state that a high loan rate can be explained by an inefficient industry.

Concerning donor dependencies, increased competition and excessive loan rates, it is crucial for the MFIs to become more efficient, but the question is how? By studying the effect of efficiency drivers, decision makers can acquire a better knowledge of where to put in effort to increase the MFIs efficiency, hence it makes our study relevant. This thesis is contributing by studying 17 variables regarding cost-efficiency - some of them barely been tested before. Moreover, by using a large global dataset with information from 379 MFIs in 74 countries, it gives validity to the results (Roy Mersland, 2009a).

1.2 Main objective of the study

The main objective of this study is to identify efficiency drivers and determine their effect on the overall efficiency of microfinance Institutions (MFIs), focusing on operational costs. This will involve indentifying elements that might affect the overall efficiency and study how these elements really affect the overall efficiency of MFIs.

1.3 Structure

This thesis is made up of six chapters, including the introduction chapter. Chapter two is an overview of the microfinance industry, presenting the concept of microfinance, participants, product and services, outreach and impact. Chapter three deals with the theoretical framework, in which bank efficiency theory, cost-efficiency theory, and a discussion of efficiency in MFIs and efficiency drivers are presented. The chapter also presents the hypotheses and the variables used. Research methodology and methods are presented in chapter four following by chapter five in which efficiency drivers are analyzed and results are presented and discussed. Finally, we bring our study to a conclusion in chapter six.

2. A MICROFINANCE OVERVIEW

This chapter gives an overview of the microfinance industry, which includes the concept of microfinance, participants, product and services, outreach, and a discussion about the true impact of microfinance.

2.1 The concept of microfinance

Microfinance is based on the idea that poor and low income people with no access to financial services through the ordinary formal financial sector, because of their limited influence and limited possibilities, still have a valuable use of financial services (Ledgerwood, 1998).

One recognized definition that is often referred to, is the one used by Robinson (2001, p. 9): *"Microfinance is defined as small-scale financial services-primarily credit and savings-provided to individuals and groups at the local levels of developing countries, both rural and urban"*. A similar but more concise definition is used by Gateway (2009): "*Microfinance is financial services for poor and low-income clients."* These definitions do not include the development objectives of microfinance, only the financial objectives. Yet, the definitions serve our purpose, focusing on the financial side of microfinance. We have decided to use the definition by Gateway (2009) throughout this thesis.

Many poor and low-income people have access to informal financial services such as commercial moneylenders, typically at a very high cost to the client. The nominal interest rates for small one-day loans can range from 5 percent to more than 20 percent per day (Robinson, 2001). Microfinance promoters highlight that access to microfinance services can reduce risk, raise productivity, diversify income opportunities, increase income, and improve the quality of poor people's lives and those of their dependents (Robinson, 2001). A common recommendation for MFIs is that they should be financially self-sufficient, independent from subsidies and locally managed (Ledgerwood, 1998). Many of the microfinance providers are struggling financially, but there are a growing number of well-documented success stories of MFIs operating in areas like rural Bangladesh, urban Bolivia or rural Mali. They are all in a strong contrast to the non sustainable and costly state-run specialized financial institutions (Ledgerwood, 1998). Data from the Microbanking Bulletin reports that 63 of the world's top

MFIs had around 2.5% return on total assets, after adjusting for inflation and subsidies (MIX, 2008).

In the last years, more attention has been put on poor and low income people's latent financial needs and their benefit of convenient, flexible and reasonably prized financial services. The industry has developed from microcredit, offering only loans, into microfinance, offering a much broader range of financial products such as microcredit, savings, insurance, money transfers and other financial products (Armendariz de Aghion & Morduch, 2005; Gateway, 2009). Actually, some argue that microfinance is an outdated term also, because of the change from being a marginal and narrow financial assistance, into becoming a commercial industry with a potential market of around 3 billion people (Helms, 2006).

2.2 Microfinance clients

Why do poor people demand microfinance? Rutherford (2000) argues that the main reason is that people need access to lump sums of money. There are particularly three reasons why they need such lump sums:

- Life cycle events: Dowries, funerals, religious feasts, rites, marriage etc.
- Emergencies: Health care, loss of work, climatic incidents, live stock diseases, loss of home (e.g. bulldozing in slum areas) etc.
- Opportunities, either business opportunities or other types of opportunities: Buy land or a TV, fluctuation in food prices (e.g. grains), livestock, machinery, bribes to get hold of opportunities, start a business, increase a business etc.

Promoters of microfinance face a great challenge in reaching people suffering from poverty, not only because of the variety of clients and their needs, but also for the variety of other poor people and potential clients (Robinson, 2001). Despite the variety, we have chosen to use "poor and low income people" from Helms (2006) as a collective term for people that microfinance promoters try to reach. Helms (2006) points out some general characteristics of microfinance clients:

- Most clients come from moderately poor and vulnerable non-poor households, with some clients from extreme-poor households also participating

- Programs that explicitly target poorer segments of the population generally have a greater percentage of clients from extreme-poor households
- Destitute households are outside the reach of microfinance programs

2.3 Providers of microfinance

There is a variety of microfinance providers ranging from informal financial arrangements to formal financial institutions (Helms, 2006). MFIs are a generic term for microfinance providers normally incorporated as member-based cooperatives, Nonprofit organizations or shareholder firms (R Mersland, 2009b). The spectrum of financial service providers are presented in table 2-1.

Figure 2-1 Providers of microfinance services

Informal			Member based		NGOs	Formal financial institutions	
Friends and family	Moneylenders	ROSCAs	CVECAs	Cooperative financial institutions	NGOs	NBFIs	State-owned banks, including postal banks
	Saving collectors	ASCAs	FSAs				Rural banks
	Traders		SHGs				Specialized MFI banks
							Full-service commercial banks

Note: ROSCAs = Rotating savings and credit associations; ASCAs = Accumulating savings and credit associations; CVECAs = Caisses Villageoises d´Epargne et de Crédit Autogérées; FSAs = Fiancial service associations; SHGs = self-help groups; NGOs = Nongovermental organizations; NFBI = nonbank financial institution.

Source: (Helms, 2006)

The Informal sector is the most common way to access financial service for poor and low-income people. Informal providers consist of friends and family, moneylenders, deposit collectors, pawnbrokers, traders, processors, input suppliers and informal member based schemes (Helms, 2006). Being informal means that it does not apply any bank law nor general commercial law, and any disagreement with the informal bank system cannot be solved by the legal system (Ledgerwood, 1998). Members-based organizations like CVECAs, FSA, SHGs and cooperative financial institutions are building on the informal system, and they both share some similarities, especially on the use of clients own savings as the main source of fund. The main difference is that member-based organizations are organized in a more formal way or promoted by formal organizations.

Between the informal arrangements and the formal financial institutions we find NGOs, which are important contributors to the microfinance market. NGOs are often associated for featuring social missions, but in the last ten years the trend has been in a more commercial direction. The rational explanation for this is often referred to as "seeking sustainability". Many of the NGOs are often donor dependent and high cost operational. In order to be more self-sufficient, many NGOs are separating the microfinance operations from other services, or transforming the organisation into regulated financial institutions. NGOs have been pioneers when it comes to innovative solutions for reaching increasingly poor and vulnerable groups and pushing the poverty frontier (Helms, 2006).

Formal financial institutions are charted by the government and are subject to banking regulations and supervision (Ledgerwood, 1998). Formal financial institutions consist of NBFIs, state-owned banks and postal banks, rural banks, specialized microfinance banks and full-service commercial banks. Especially state-owned banks have an unfortunate history in the microfinance market, but in spite of all the challenges have many formal financial institutions, inclusive state-owned banks enormous potential for making financial system truly inclusive. The main advantages are larger size, wide branch networks, wide range of services, and funds to invest in banking systems and skills (Helms, 2006).

2.4 Products and services

Credit service

Microcredit or small-scale lending is probably the most well-known service provided by MFIs. The MFIs lend out credit, mostly for productive purposes but also for consuming, and other purposes, to people that normally do not have access to loans from the formal financial market (Ledgerwood, 1998). MFIs have in general three ways of lending out money, either to individuals, groups or village banks. An individual loan methodology can be explained as credit lend out to individuals that is not member of a group with joint liability for the loan repayment. By combining the methods for lending decisions from formal financial institutions and informal sector lenders, the MFIs has manage to successfully developed effective models for individual lending (Ledgerwood, 1998). Group lending is another loan methodology and consists of groups of people who have a joint interest to enter the financial market. Clients are organized into small groups of 5-10 members and given individual loans within the groups. All members share a joint liability for each loan which substitutes the requirements of collateral. The group lending model has met some critics because of situations where groups tend to exclude the poorest because of the pressure to repay the loan (Hulme & Mosley, 1996). The third loan methodology is the "Village Banking model". MFIs organize clients into larger groups between 30-100 members and lend out credit to the group itself rather than to individuals, and the group is given the responsibility to distribute credit out to each member (Ledgerwood, 1998).

Saving service

Micro-saving or small-scale saving is provided by the MFIs to enable poor and low-income people to save money safe, and to get some return on their money. It is common to distinguish between two types of savings, compulsory savings and voluntary savings. Compulsory savings works as a collateral for the loan received, and it can also be considered as a part of a loan product rather than an actual savings product. These strings attached to compulsory savings have met some criticism and dissatisfaction, much because of the locked access to the funds (Armendariz de Aghion & Morduch, 2005; Ledgerwood, 1998). Voluntary savings is the other saving type. It is provided by the MFIs to borrowers and also non borrowers, and it is a lot more user-friendly service then compulsory savings. However, voluntary savings struggles with high administrative complexity and costs, especially for smaller saving amounts, and the MFIs face many challenges on their way of offering voluntary savings (Ledgerwood, 1998). Ledgerwood (1998) points out that savings are useful to:

- Demonstrate the value of savings practice to borrowers.
- Serve as additional guarantee mechanism to ensure the repayment of loans.
- Demonstrate the ability of clients to manage cash flow and make periodic contributions.
- Help to build up the asset base of clients.

Insurance service

Micro-insurance is provided by the MFIs to enable poor and low-income people reducing their financial risk, in cases like illness, injuries, extreme weather or fatalities. The most common products offered by the MFIs are life insurance and health insurance, and to some extend property and crop insurance. Life insurance has until now been the most successful insurance product (Armendariz de Aghion & Morduch, 2005). It has not been easy developing insurance products that fit the needs of poor people, and also makes it economical sufficient for the MFIs. One of the main challenges is to overcome problems of adverse selection and moral hazard. Governmental attempts have turned out to be inefficient and largely non remunerative and informal mechanism has been a very costly alternative. Micro-insurance products does not have the same widespread as microcredit and micro-lending, but there is a growing demand by the poor and low-income and it is expected to be offered more extensively by the MFIs in the future (Ledgerwood, 1998).

Credit cards and payment services

Credit cards and payment services are in an early phase of development and to this date only offered by a few MFIs, anticipated to be a lot more recognized in the future. Offering credit cards is a step in the right direction of giving poor and low-income people simplified and user-friendly financial services, with expected advantages such as streamline operations and an ongoing line of credit, enabling them to supplement their cash flow according to their needs. The MFIs can also benefit from it, expecting lower administrative and operating costs. Yet, it is still early to say if it is going to be a success or not. Payment service includes check cashing and check writing privileges, money transfer and remittance of funds within and across countries. The MFIs offering payment services do not require larger transaction amounts such as formal financial institutions often do (Ledgerwood, 1998).

Nonfinancial service

Some MFIs also provide poor and low-income people with nonfinancial service, meaning social intermediation, enterprise development and other social services such as health, nutrition, education and literacy training. One argument for mixing financial and nonfinancial service is that economical disadvantages often are accompanied by social disadvantages. However, it is a great challenge to make nonfinancial services profitable, and except for some service fees, nonfinancial services mostly depend on subsidies. Another problem is that many

MFIs integrate nonfinancial services with financial service, which makes it difficult to measure and control the self-sufficiency of the financial services (Ledgerwood, 1998)

2.5 The outreach and impact of microfinance

There have been several attempts to count the number of credit clients served by MFIs worldwide. Christen (2004) estimates the total number of credit clients to be 152 millions. WSBI counted 190 million credit clients in 2005, but they also included savings banks in their estimate. Microcredit Summits (2007) annual report presented an estimate of 133 million credit clients worldwide. They also reported that almost 90 percent of those clients are served by only 67 institutions. Microbanking bulletin (2008) are summing up highlights from 890 MFIs, reaching over 64 million clients. The highlights are presented in table 2-2.

Table 2-1: Highlights from 891 MFIs

	Offices ('000)	Employees ('000)	Borrowers ('000)	Depot Accounts ('000)	Loan Portfolio (USD '000 000	Deposit (USD '000 000)
Africa	4	35	5 183	8 036	2 419	1 9848
Asia	23	200	43 294	11 769	6 744	1 163
ECA	3	39	2 387	3 891	7 776	3 296
LAC	9	77	11 374	9 816	13 820	8 637
MENA	2	16	2 244	9	1 040	55
Globe	**42**	**366**	**64 482**	**33 520**	**31 798**	**15 098**

Source: (Mix & eXchange, 2007)

Note: BRI is not included in this survey. Its conclusion would bring global deposits and deposits accounts to the same scale as the lending side.

Microfinance has in the latest years been fronted as the "silver bullet" in the fight against poverty. However, there are some disagreement about the overall effect and the beneficial extend of microfinance (Dichter, 2003). Karnani (2008) has analyzed macroeconomic data and argues that microfinance can actually impact the country's economy in a less good way compared to job creation and tax revenue. Further he argues that poor people and the society as well will be better off if they are offered a place of employment rather than being pushed into entrepreneurship. Morduch (1998) found no evidence in his survey to support claims that the microfinance programs in Bangladesh increase consumption levels or increase educational enrolments for children relative to levels in the control villages. He says "*Tens of millions of dollars worth of subsidized resources support these programs and the question now is* *whether these benefits are justified by their substantial costs."* A few studies have also found that the burden of dept could have a negative impact on poverty reduction (Hulme & Mosley, 1996; McGuire & Conroy, 2000). Microfinance has also been criticized for not having the ability to reach the poorest of the poor, providing services not suitable for their needs (CGAP, 2009b), and Skarlatos (2004) argues that social needs must be ensured before poor people can benefit from microfinance services.

However, it is a wide agreement about the positive impact on the every-day life of millions of poor and low income people. Copestake et.al (2001) found from a case study in Zambia that it was a positive link between microfinance participation and household growth. They also found that 52% of the borrowers that where asked, had improved their overall quality of life. Some positive impacts that microfinance have on poor and low income people are pointed out (CGAP, 2009b):

- Increasing income and smooth out cash flows.
- Building up assets.
- Reducing vulnerability and allow household to better planning for the future.
- empowering women and improve their status within the family and the community.

3. EFFICIENCY THEORY AND HYPOTHESIS

This chapter presents the theoretical framework applied for the study, which includes a review of efficiency theory and a discussion about the efficiency in MFIs. The chapter also propose hypothesis and define variables.

3.1 Efficiency theory

Bank literature pays a great deal of attention to the performance of banks (Athanassopoulos, 1997; Bala & Cook, 2003; Brockett, Cooper, Golden, Rousseau, & Wang, 2004; Dekker & Post, 2001; Hartman, Storbeck, & Byrnes, 2001; Kuosmanen & Post, 2001; Luo, 2003; J. M. Pastor, Pérez, & Quesada, 1997; Pille & Paradi, 2002; Schaffnit, Rosen, & Paradi, 1997). This is because better performing financial institutions may improve cost, revenue and financial results. Most researchers review banking literature and theory when studying efficiency in microfinance institutions (Begoña Gutiérrez-Nieto, Serrano-Cinca, & Mar Molinero, 2007b; Lafourcade, Isern, Mwangi, & Brown, 2005; Qayyum, 2006). MFIs efficiency performance can be measured by same financial performance measures applied in the bank literature (Brau & Woller, 2004).

Economic theory assume that production takes place in an environment in which managers attempt to maximize profits by operating in the most efficient manner possible (Evanoff & Israilevich, 1991). The competitive model suggests that firms that fail to do so will be driven away by more efficient ones. Efficiency is using available resources in such a way that we maximize production of goods and services (O'Sullivan & Sheffrin, 2003). A system can be called economically efficient if:

- Nothing can be made better off without making something else worse off.
- More output cannot be obtained without increasing the amount of inputs.
- Production proceeds at the lowest possible per-unit cost.

The overall efficiency of banks can be decomposed into scale efficiency, scope efficiency, technical efficiency, and allocate efficiency. Scale efficiency deals with operation in the range of constant return to scale. The potential productivity a bank would gain by achieving optimal size of the firm. Scale economies are when average costs decline as bank output rises. This results from spreading fixed costs over greater volume of output (DB Humphrey, 1990). Economies of scale primarily refer to supply-side changes. Still, it is important to be aware of limits. Miller and Noulas (1996) find that the majority of banks in USA are too large, having moved into the region of decreasing return to scale. Scope efficiency deals with operation in different diversified areas, where producing two or more product lines in one firm is less costly than to produce them separately (Panzar & Willig, 1981). Economies of scope refer to demand side change such as increasing/decreasing scope of/and distribution of different products. Technical efficiency represents the capacity and willingness of an economic unit to produce the maximum attainable output from a given set of input and technology (Koopmans, 1951). Allocate efficiency occurs when inputs are combined in optimal proportions (Evanoff & Israilevich, 1991).

The shareholders of a bank have right to claim profits, and it is in their interest to maximize profit. This can be achieved by maximizing revenue and/or by minimizing costs. If the assumptions under perfect competition hold, we are forced to exclude revenue maximizing which makes profit maximizing equivalent to minimizing costs. Berger and Mester (1997) suggest cost efficiencies as one of the most important economic efficiency concepts. Perfect competition can hardly be fulfilled in reality due to regulations and imperfect competition. Yet, the competition is getting harder in the microfinance market. An MFIs cost function can be represented by Berger and Mester (1997):

$$\ln C = f(w, y, z, v) + \ln \mu_c + \ln \in_c$$

Where C is the variable costs, f denotes some functional form, w is the vector of prices of variable inputs, y is the vector of quantities of variable outputs, z is the quantities of any fixed net puts, v is the set of environmental or market variables that may affect performance, μ_c is the inefficiency factor that may raise costs above the best practice level, and $\in_c$ is the Random error plus measurement error and luck that may temporarily give banks higher/lower cost.
By using the cost function of a MFI denoted as MFI*b* it can compare its efficiency level against the cost function of a best practice MFI producing the same output bundle under the same conditions. The following function can be applied (A. N. Berger & Mester, 1997):

$$EFF^{b}=\frac{\hat{C}^{min}=\exp\left[\hat{f}(w^{b},y^{b},z^{b},v^{b})\right]\times\exp\left[\ln\hat{u}_{c}^{min}\right]}{\hat{C}^{b}=\exp\left[\hat{f}(w^{b},y^{b},z^{b},v^{b})\right]\times\exp\left[\ln\hat{u}_{c}^{b}\right]}$$

The numerator explains the estimated cost that it is need for MFI*b* to produce its output vector if it was efficient as the best practice MFI facing the same exogenous variables (w,y,z,v). The denominator explains the true cost of MFI*b*. For example, a MFI with a cost-efficiency of 0.70 would indicate that it is wasting 30% of their costs, being only 70% effective compared to the best practice MFI. The ratio ranges from $[0,1]$.

3.2 Efficiency in MFIs

Microfinance is considered an important poverty alleviation tool. However, providing credit to the poor and low income people generally proves to be a very costly activity and providers of microfinance services are often loss making and not financially sustainable (Murdoch, 2000). This is partly due to the high transaction costs in terms of screening, monitoring of borrowers and related back-office administrative costs (Hulme & Mosley, 1996). Poor and low income people lend smaller amounts of money and the individual transactions are relatively small. A typical loan size can be 50 USD or even less for some institutions (Hardy, Holden, & Prokopenko, 2003). Moreover, poor and low income people have limited possibilities to inform about their creditworthiness and put forward collateral. Focus on decreasing transaction costs should be emphasized for the MFIs in order to increase profitability and become self-sufficient. Transaction costs arise primarily due to the limits of human ability to process information. "*Despite whatever intentions economic actors may have to act rationally and far-sighted, the limitations on gathering, processing and communicating information constrain how rationally individuals can act*" (Macher & Richman, 2008, p. 3). There are three main sources of transaction costs. First of all individuals are limited in their ability to plan for the future. They lack the knowledge, foresight or skill to plan for all contingencies that may arise (Simon, 1957). Second,

contracting parties have difficulties developing a common language to describe the actions and states of the world. This is often due to lack of information (Hart, 1995). Third, it is often difficult for parties to communicate their plans in such a way that a uniformed third party (e.g. a court) can reasonably enforce them (Lewis & Sappington, 1991).
Lack of modern technology, particularly in remote and rural areas, is a huge challenge for MFIs regarding cost-effective operations. Low population density, poor communication infrastructure and remoteness combined with low technology is associated with high transaction costs and covariant risks (Bank, 2003; Johnson, Malkamaki, & Wanju, 2005). However, if the MFIs can manage to make use of technological developments such as credit cards, ATMs, cell phones and internet, they can reduce costs and operate in a more efficient way (Hermes, et al., 2008). Fortunately, modern technology has expanded rapidly in developing countries. For example, 82 percent of the last 2 billion cell phones were sold in developing countries (Pasricha, 2008). Purchase transactions using credit cards (instead of cash) have also been growing fastest in developing countries (Honohan & Beck, 2007).

Being self-sustainable is a major challenge in the microfinance industry, and many of the MFIs are depending on donors (R Mersland & Strøm, 2008a). A self-sustainable MFI is able to repay the opportunity costs of all inputs and assets with its generated income (Chaves & Gonzalez-Vega, 1996). Many argue that is only a short-term solution depending on donors, and MFIs can only exist in the long run if they can liberate from donors and become self-sustainable (Arsyad, 2005; Maddison, 2006). It is also argued that the solution to expand MFIs globally depends on MFIs becoming self-sufficient (Drake & Rhyne, 2002; Robinson, 2001). Research suggests that presence of subsidies increases MFI costs because it removes pressure from the management that would otherwise force them to increase efficiency (Armendariz de Aghion & Morduch, 2005; Valentina Hartarska, Caudill, & Gropper, 2006a). Hardy et.al (2003) argues that subsidies should be restricted to only one-time support to cover the start-up costs in MFIs since ongoing support is likely to increase moral hazard and poor management. Nevertheless, donors have played an important key role in the microfinance industry, especially in the start-up of MFIs, funding the systems and staff capacity (CGAP, 2003a). Most donors are also monitoring the MFIs to verify that their donations are used in accordance with their wishes, and this can help improve the performance of MFIs (Fama, 1983).

Poor and low income peoples lack of collateral and the high cost of providing small loans in remote and rural areas are reflected in high nominal interest rates provided by the MFIs (Armendariz de Aghion & Morduch, 2005; CGAP, 2009c). Low efficiency can make interest rates higher than necessary and attention to reducing operating costs should be emphasized in order to achieve competitive interest rates (CGAP, 2003a). We demonstrated earlier in the introduction, building upon Hulme and Mosley (1996, p. 19), that the loan rate is much affected by the MFIs administrative cost. Gonzalez (2007) reports that operational costs represent about 2/3 of charges to borrowers, making them the largest component of the interest rates. Attention should be emphasized towards identifying their drivers and quantifying them in order to improve efficiency in MFIs. Increased efficiency can contribute to decrease the cost of credit to the poor and low-income people, making lending more beneficial.

3.3 MEASURING EFFICIENCY

Coelli (2005, p. 5) states that "*If information on prices is available, and a behavioral assumption, such as cost minimization or profit maximization, is appropriate, then performance measures can be devised which incorporate this information.*" Efficiency performance measures are indicating how well an institution is managing its operations. They are providing information about the rate at which MFIs generate revenue in order to cover their expenses (Ledgerwood, 1998). By comparing their efficiency performance over time and against competitors, MFIs can determine how well they are exploiting their resources and where to make improvements in their operations. While productivity indicators reflect the amount of output per unit of input, efficiency indicators take into account the cost of inputs and/or the price of outputs (Microrate & Bank, 2003). We are focusing on the MFIs operational cost which can be defined as: *"expenses related to the operation of the Institution, including all the administrative and salary expenses, depreciation and board fees"* (Microrate & Bank, 2003, p. 16). Operating cost have also been studied in the bank literature by Athanassoupoulos (1997), Pastor (1999),Worthington (1998), Laeven (1999). Three frequently used measures of cost-efficiency will be presented in the following. These will be our dependent variables when identify efficiency drivers and determine their effect on the overall efficiency of MFIs.

Operating expense to portfolio ratio

Operating expenses to portfolio ratio (OEP ratio) can be used as a measure of cost-efficiency and it is frequently used in the microfinance literature (Ledgerwood, 1998). The OEP ratio indicates the cost needed for the MFI to operate one unit of its portfolio. The ratio ranges from 0 to 1 where a ratio close to zero indicates a highly efficient MFI. Considering the size of the portfolio, larger MFIs can compare its cost level with smaller MFIs. Ahmed and Munir (2006) and Gonzalez (2007) use the OEP ratio in their papers on financial efficiency, and the rating agencies highlight the ratio in their reports. The following variable is used as a measure of the OEP ratio (Roy Mersland, 2009a):

$$\text{OEP ratio} = \frac{\text{Operating expense}}{\text{Average gross portfolio}}$$

Operating expense to asset ratio:

The operating expense to asset ratio (OEA ratio) indicates the cost needed for the MFI to operate one unit of its assets. The ratio ranges between 0 and 1. The MFIs assets can include cash, bank deposits, investments, fixed assets or portfolio. MFIs that have a large amount of its capital in non productive assets such as fixed assets, land or property can be less efficient in helping the poor since it is the loan portfolio that poor and low-income people benefit from. Gonzalez (2007) finds that there is a strong relationship between cost reduction and gross loan portfolio to assets. His research implies that a 10 percent increase in gross loan portfolio to assets yields a 7 percent decrease in costs. Vanguri (2008) suggests from his research on capital allocation in MFIs, that allocating more capital towards loan portfolio will yield better returns. Berger and Humphrey (1997) review 130 studies on financial institutions and suggest that banks that have high loans to assets ratios tend to have higher profit efficiency. The value of assets has been included in financial efficiency models by Luo (2003), Seiford and Zhu (1999) . In the banking industry, the ratio of operating expenses to the value of total assets is an accepted indicator of unit operating costs (D Humphrey, Willesson, Bergendahl, & Lindblom, 2006). The following variable is used as a measure of the OEA ratio (Roy Mersland, 2009a):

$$\text{OEA ratio} = \frac{\text{Operating expense}}{\text{Average total assets}}$$

Cost per Credit client

Cost per credit client (CC) or cost per borrower indicates the average cost of providing an active credit client (Microrate & Bank, 2003). It is different from the two other efficiency measures since it is not a ratio but an absolute value measured in USD. Donors and investors pay special attentions to the cost per client since it indicates the cost of reaching out to one more client. However, measuring efficiency only by looking at the cost of maintaining an active credit client can give an incomplete picture. A low indicator can indicate that MFIs are putting little resources into screening and monitoring borrowers. In their paper on financial performance in Africa, Lafourcade et.al (2005), use cost per borrower as a measure of efficiency. Their findings conclude that MFIs achieve higher efficiency by keeping cost per borrower low. This is also supported by Ahmad and Munir (2006) and Mersland and Strøm (2008a). UNCDF (2005) states that efficiency should preferably be measured through cost per borrower. The following variable is used as a measure of the dependent variable (Roy Mersland, 2009a):

$$\text{CC} = \frac{\text{Operational expense}}{\text{Credit clients}}$$

3.4 EFFICIENCY DRIVERS, HYPOTHESES AND VARIABLES PRESENTATION

This section presents a literature review and a discussion about the efficiency drivers. We are also presenting our hypotheses and the variables we are using to measure efficiency drivers. This section also explains the concept of using statistical hypothesis and dummy variables.

In statistical theory a hypothesis is an unproven proposition or supposition that tentatively explains certain facts or phenomena. A hypothesis is a statement, an assumptions about the nature of the world (Zikmund, 2000, p. 459). The classical hypotheses consist of a null hypothesis and an alternative hypothesis, generally notated as H_0 for the null hypothesis and H_A for the alternative hypothesis. A Null hypothesis is typically not the expected results. It is often a conservative statement, expecting changes in the results to be entirely due to random errors. The purpose for a null hypothesis is to provide an opportunity to nullify it. In our study we will have null hypothesis stating that the tested efficiency driver actually has no effect on the MFIs overall efficiency. The alternative hypothesis, expected to be the true one, state that the tested efficiency driver has an effect on the MFIs overall efficiency (Greene, 2003;

Studenmund, 2006; Zikmund, 2000). Regression models, analysis and hypothesis testing will be presented later in the following chapters.

Applying dummy variables can be useful in order to explain if a sample meets a particular condition or not. It has two distinct levels which are coded 0 and 1 (Studenmund, 2006; Zikmund, 2000).

$$\text{A dummy variable } D_i = \begin{cases} 1 \text{ if the } i\text{th observation meets a particular condition} \\ 0 \text{ otherwise} \end{cases}$$

As an example, if we want to know the gender of a person, we can make use of a dummy variable equal 1 for female and 0 otherwise. Both genders are explained by one variable; if it is not a female, then it has to be male. *The event not explicitly represented by a dummy variable, the omitted condition, forms the basis against which the included conditions are compared (Studenmund, 2006, p. 222).* Dummy variables can also be useful to represent variables with more than two alternatives. For example, if we want to measure if it is a child, adult or elderly person, it would be wrong to have one variables ranging from 0 to 2. We have no reason to think that if an elderly is equal to 2 it is then twice the size of an adult equal to 1. The solution would be to create two dummy variables, one to explain if it is a child (or otherwise), and another one to explain if it is an adult (or otherwise). The third alternative whether it is an elderly (or otherwise), will be explained by comparing the two included variables.

Credit officer productivity

Credit officer or loan officer productivity states the number of credit clients per loan officer in a MFI. A credit officer can be defined as *"personnel whose main activity is direct management of a portion of the loan portfolio"(Microrate & Bank, 2003, p. 22).* Arsyad (2005) suggests that the efficiency of MFIs increases if they can manage to increase credit officer productivity. Increasing average loan size or number of clients per credit officer will increase credit officer productivity. A positive and very significant impact on efficiency is also supported by Luzzi and Weber (2006). However, too many clients per credit officer may result in higher loan losses (Ledgerwood, 1998). In line with Luzzi and Weber (2006) and Arsyads (2005) findings we propose the following hypothesis:

Hypothesis 1: Credit officer productivity

$H1_0$: $H1_A$ is not true.

$H1_A$: Increased credit officer productivity has a positive effect on the MFIs overall efficiency.

The following variable is used as a measure of credit officer productivity (Roy Mersland, 2009a):

$$\text{COProd} = \frac{\text{Total number of credit clients}}{\text{Total number credit officers}}$$

Competition

In the recent years competition among MFIs has increased rapidly. Additionally, commercial banks have become more interested in providing microfinance services due to the high levels of profitability among some MFIs in the recent years (Hermes, et al., 2008). It is reasonable to believe that the microfinance industry and especially the clients will gain from increased competition. However, it seems to be some disagreements about the effect on the MFIs efficiency. Gorton and Winton (2003) argues that competition may undermine the long-time customer relationship, and lead to time consumption and increased cost in order to keep the customer and maintain the relationship, which suggests that increased market competition will decrease the efficiency in MFIs. Moreover, Luzzi and Weber (2006) show that number of competitors has a strong negative influence on financial performance. Also, McIntoch (2005) argues that entrance of competitors in the Ugandan microfinance market led to a decline in loan repayment and exit of larger borrowers. This is also supported by similar findings in Bolivia (Sengupta & Aubuchon, 2008), and Thailand (Ahlin & Townsend, 2007). However, in the recent years institutions have started to share information about borrowers, which has led to strengthen in dynamic incentives and an increase in the client base. The MFIs seem to adjust to the increased competition. Mersland and Strøm (2009d) find a significant increase in performance with an increase in competition, since new entrants force the MFIs to drive down cost and increase efficiency in order to survive in the market. Similar findings were reported by the Asian development bank's research on MFIs in the Philippines (Fernando & Nimal, 2004). This is also supported by Rhyne and Otero (2006) and Nickell et.al (1997). Based on the preceding discussion we expect the market competition to have an effect on the MFIs overall efficiency. Yet, we are uncertain about the direction. The following hypothesis is presented.

Hypothesis 2: Market competition

$H2_0$: $H2_A$ is not true.

$H2_A$: Market competition has an effect on the MFIs overall efficiency.

The variable used in this study to measure market competition is made up of subjective judgments based on general competition information provided in the rating reports. It is only a rough guide to the relative competition pressure in the microfinance markets. The market competition scale is ranging from 1 to 7 points, where 1 is little or no competition and 7 is high competition (Roy Mersland, 2009a). There are two subjective judgments of the MFIs market competition in the dataset, so we have decided to use the average value of those two. The following formula is used as a measure of market competition:

$$\text{MC} = \frac{\text{Market competition I} + \text{Market competition II}}{2}$$

<u>Pure financial service</u>

Most MFIs are specialized into only providing financial services, while others also provide non-financial services such as social intermediation, enterprise development, health, nutrition, education and literacy training (Ledgerwood, 1998). Luzzi and Weber (2006) suggest that number of services will affect financial performance, but they are not able say anything about the direction of this influence. Lensink and Mersland (2009c) find that MFIs only offering financial services are more efficient than MFIs combining financial services with social services. In accordance with the findings of Lensik and Merlsand (2009c) we propose the following hypothesis:

Hypothesis 3: Pure financial services

$H3_0$: $H3_A$ is not true.

$H3_A$: Providing pure financial services has a positive effect on the MFIs overall efficiency.

The following variable is used (Roy Mersland, 2009a):

$$\text{PureFS} = \begin{cases} 1 \text{ if the MFI only provide financial services} \\ 0 \text{ otherwise} \end{cases}$$

<u>Age</u>

CGAP (2009a) suggest three reasons why older MFIs are more efficient then younger MFIs; higher numbers of loans may drive scale economies, higher average loan sizes may improve the cost structure, and more knowledge about customers may streamline processes. Gonzales (2007) shows that MFI efficiency is strongly related to age and that efficiency increases substantially over the years. Still, he implies that growing beyond 2000 customers has no significant efficiency gain that can point in the direction of scale economies. This can be explained by a learning curve. When the customer base is build up, and most internal processes have been tested and improved the trend begins to level off. Moreover, Coleman (2007) finds that ageing MFIs increase loan losses because they have to grant credit to new customers who may not be as creditworthy as its present customer-base. In line with what CGAP (2009a) suggest we propose the following hypothesis:

Hypothesis 4: Age

$H4_0$: $H4_A$ is not true.

$H4_A$: MFIs increase their overall efficiency when ageing.

MFIs age can be calculated by subtracting the year of start-up with MFI activities from the year of rating. The following variable is used for studying age as an efficiency driver:

$$\text{Age} = \text{Year}_{\text{rated}} - \text{Year}_{\text{start-up}}$$

<u>Loan methodology</u>

MFIs have as explained in chapter two in general three ways of lending out money, either to individuals, groups or village banks. Hermes et.al (2008) find results indicating that group lending is less costly due to reduced information costs attended with the joint liability arrangement. This is also supported by Hartarska et.al (2006a). On the other hand, individual lending method yields the highest average profit and it is largely favorable considering the high loan size per borrower (Cull, Demirguc-Kunt, & Morduch, 2007; R Mersland & Strøm, 2008a). It is important to notice that individual lending increases the cost per client but reduces the OEP and OEA ratio. It is more expensive to service a larger loan than a small one. In other words, individual lending reduces costs relatively, but not in absolute terms. In line with Cull et.al (2007) and Mersland and Strøm (2008a) findings we propose the following hypothesis:

Hypothesis 5: Loan methodology

$H5_0$: $H5_A$ is not true.

$H5_A$: Individual lending will decrease OEP and OEA ratio and increase cost per client compared to group and village lending.

Many MFIs provide both individual lending and group lending, but only the main loan methodology is registered in our variables. We have converted one variable ranging from point 1 to 3 (1 for Village banking, 2 for Solidarity group lending and 3 for individual lending), into two dummy variables. The following definitions are used:

$$VG = \begin{cases} 1 \text{ if the main loan methodology is village banking} \\ 0 \text{ otherwise} \end{cases}$$

$$SG = \begin{cases} 1 \text{ if the main loan methodology is solidarity group lending} \\ 0 \text{ otherwise} \end{cases}$$

The following dummy variable will be excluded from the model:

$$IL = \begin{cases} 1 \text{ if the main loan methodology is individual lending} \\ 0 \text{ otherwise} \end{cases}$$

Urban versus rural markets

MFIs can roughly operate in urban or rural markets, or both. It is reasonable to expect higher input prices in urban areas, especially on labor, which should suggest a less efficient market to operate in. However, lower technology and lower population density in rural makes should suggest otherwise. Luzzi and Weber (2006) find that rural intervention is positive for the outreach but negative for the financial performance of the MFIs. This indicates that MFIs operating in rural areas are less efficient then MFIs operating in urban areas. In accordance with Luzzi and Weber (2006) we propose the following hypothesis:

Hypothesis 6: Urban versus rural markets

$H6_0$: $H6_A$ is not true.

$H6_A$: Urban markets are the most efficient markets for the MFIs to operate in.

We have converted one variable ranging from point 1 to 3 (1 for urban areas, 2 rural areas and 3 for urban and rural areas) into two dummy variables. The following definitions are used:

$$\text{Urban} = \begin{cases} 1 \text{ if the MFI is operating in urban areas} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{Rural} = \begin{cases} 1 \text{ if the MFI is operating in rural areas} \\ 0 \text{ otherwise} \end{cases}$$

The following dummy variable will be excluded from the model:

$$\text{UaR} = \begin{cases} 1 \text{ if the MFI is operating in urban and rural areas} \\ 0 \text{ otherwise} \end{cases}$$

Performance pay

Some MFIs pay the credit officers based on their financial performance (Roy Mersland, 2009a). Therefore it is reasonable to expect that performance pay improve the efficiency of MFIs. Holtmann (2002) asserts that highly productive MFIs often have incentive schemes. Yet, the designs of the schemes are different among MFIs. Holtmann (2002, p. 2) says: "*There is little dispute among microfinance practitioners that well-designed staff incentive schemes can have positive and powerful effects on the productivity and efficiency of MFI operations.*" However, he also point out that incentives schemes in MFIs have little empirical research to rely on. After introducing a performance-based bonus system for the loan officers, productivity improved significantly and now stands at the top of the industry with 644 outstanding clients per loan officer (Farrington, 2000). Increased credit officer productivity can relate to increased efficiency. Based on Holtmann (2002) and Farrington (2000) we state the following hypothesis:

Hypothesis 7: Performance pay

$H7_0$: $H7_A$ is not true.

$H7_A$: Performance pay has a positive effect on the MFIs overall efficiency

The following variable is used (Mersland):

$$\text{PerP} = \begin{cases} 1 \text{ if the MFI is offering performance pay} \\ 0 \text{ otherwise} \end{cases}$$

Personal expenses per employee

Personnel expenses are one of the main components of operational costs. Low salary costs increases efficiency and decreases OEP ratio. Arsyad (2005) shows that low salary costs leads to higher efficiency. This is also supported by Hermes et.al (2008). However Cull et.al (2007) finds that labor costs are positively correlated with financial performance indicating that increasing labor costs increases efficiency. This can be due to high monitoring and screening of clients that lend larger amounts. In accordance with Arsyad (2005) and Hermes et.al (2008) we propose the following hypothesis:

Hypothesis 8: Cost per employee

$H8_0$: $H8_A$ is not true

$H8_A$: Lower cost per client will increase the MFIs overall efficiency.

The variable is calculated by using the following formula (Roy Mersland, 2009a):

$$\text{CE} = \frac{\text{Personell cost}}{\text{Total employees}}$$

Average outstanding loan

Mixmarket defines average outstanding loan amount as: *"the outstanding principal balance of all of the MFI's outstanding loans including current, delinquent and restructured loans, but not loans that have been written off. It does not include interest receivable"*. MFIs incur high costs due to the high transaction costs in terms of screening, monitoring of borrowers and related back-office administrative costs (Hulme & Mosley, 1996). In order to be able to cover these costs, MFIs are often tempted to increase loan size. Gonzales (2007) implies that increasing loan size makes lending more efficient. Further, he suggests that loan size is one of the main drivers of OEP. Similar results are found in Hartarska et.al (2009). The number of loans outstanding is used as an output by Berger and Humphrey (1997) and Tortosa-Ausina (2002). Mersland and Strøm (2008a) indicate that inefficient MFIs need to shift their loan portfolios towards larger average loans in order to increase efficiency. It is important to notice that increased LOA increases the cost per client but reduces the OEP and OEA ratio. It is more expensive to service a larger loan than a small one. In other words, increasing loan outstanding average reduces costs relatively, but not in absolute terms. Based on the findings we propose the following hypothesis:

Hypothesis 9: Loan outstanding average

$H9_0$: $H9_A$ is not true.

$H9_A$: Higher LOA will decrease OEP and OEA ratio and increase cost per client.

The variable used to study the effect of average outstanding loan amount is calculated by using the following formula (Roy Mersland, 2009a):

$$\text{LOA} = \frac{\text{Gross outstanding portfolio}}{\text{Number of active credit clients}}$$

Credit officer ratio

Credit officers are those that have direct relationship with the clients. They identify clients, screen them and give follow-up and monitoring. The higher the share of the staff being credit officers, the more efficient the MFI should be. For example, Baumann (2004) uses credit officer ratio as a measure of productivity in his paper on performance of MFIs in South

Africa. Similarly Microrate and Bank (2003) suggest using the credit officer ratio when analysing the efficiency of MFIs. In line with Baumann's (2004) findings we propose the following hypothesis:

Hypothesis 10: Credit officer ratio

$H10_0$: $H10_A$ is not true.

$H10_A$: Higher credit officer ratio will increase the MFIs overall efficiency.

The variable us calculated by using the following formula (Roy Mersland, 2009a):

$$CO = \frac{\text{Total number of credit officers}}{\text{Total number of employees}}$$

MFI Size

The size of an MFI can be measured by its total assets. Humphrey (1987) finds evidence that as size of an financial institution changes, so does average cost of operations implying that efficiency increases from economies of scale. They are able to spread costs over a larger volume (DB Humphrey, 1990). However, Gonzales (2007) finds that there are limits to scale economies suggesting that scale economies in MFIs have a U-form where little efficiency effect comes from increased scale after reaching 2000 customers. Munir and Ahmad (2006) find that size of a MFI is significant and positively correlated with efficiency measures implying that as size of an MFI increases, costs decrease due to scale of economies. In line with Munir and Ahmad (2006) among others we propose the following hypothesis:

Hypothesis 11: MFI size

$H11_0$: $H11_A$ is not true

$H11_A$: MFI size has a positive or negative effect on the MFIs overall efficiency

Size of the MFI states the size of the MFIs measured by logarithm of total assets. The following definition is used:

$$\text{Size} = \log(\text{Assets})$$

Control variables

Human development index (HDI) index is a measure of human development in each country. It measures the average achievements in a country based on three dimensions of human development; Health, knowledge and life standard measured by the GDP per capita (Nations, 2007). We believe that the HDI variable can balance the USD purchasing power between countries. A country with high USD purchasing power is expected to have a low HDI. Zeller et.al (2000) among others used the HDI index in their research.

Regional control variables state the MFIs operating region. We add regional control variables to our regression models to see if there are differences in the efficiency between regions. Regional control variables are also used in research by Hartarska and Nadolnyak (2007) and Zacharias (2008). We converted the country variable found in the dataset into five dummy variables, sorted by regions. The following definitions are used:

$$\text{EECA} = \begin{cases} 1 \text{ if the MFI is operating in Eastern Europe or Central Asia} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{MENA} = \begin{cases} 1 \text{ if the MFI is operating in Middle East or North Africa} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{Asia} = \begin{cases} 1 \text{ if the MFI is operating in Asia} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{Africa} = \begin{cases} 1 \text{ if the MFI is operating Africa} \\ 0 \text{ otherwise} \end{cases}$$

The following dummy variable will be excluded from the model:

$$\text{LA} = \begin{cases} 1 \text{ if the MFI in Latin America} \\ 0 \text{ otherwise} \end{cases}$$

Table 3-1: Variables summary

Variable(s)	Definition	Hypotheses
Dependent variables		
OEP ratio (Operating expense to portfolio ratio)	Operating expense / Average outstanding portfolio	
OEA ratio (Operating expense to assets ratio)	Operating expense / Average outstanding assets	
CC (Cost per credit clients)	Operating expense / Credit clients	
Independent variables		
COProd (Credit officer productivity)	Credit clients / Credit officers	-
MC (Market Competition)	(Market competition I + market competition II) / 2	+ or -
PureFS (Pure Financial Service)	Dummy variable (1,0)	-
Age	year rated - year started	-
VB (Village Banking)	Dummy variable (1,0)	+ and -*
SG (Solidarity Groups)	Dummy variable (1,0)	+ and -*
IL (Individual Lending)	Dummy variable (1,0)	-
Urban	Dummy variable (1,0)	-
Rural	Dummy variable (1,0)	+
UaR (Urban and Rural)	Dummy variable (1,0)	+
PerP (Performance Pay)	Dummy variable (1,0)	-
CE (Cost per employee)	Personnel cost / Employees	+
LOA (Loan Outstanding Average)	Average outstanding loan amount / Credit clients	- and +*
CO ratio (Credit officer ratio)	Credit officers / Total employees	-
Size	Log of assets	-
Control variables		
HDI (Human Development Index)	HDI	
MENA	Dummy variable (1,0)	
EECA	Dummy variable (1,0)	
LA	Dummy variable (1,0)	
Asia	Dummy variable (1,0)	
Africa	Dummy variable (1,0)	

+ if the independent variable increases (decreases) then the dependent variables increases (decreases).

- if the independent variable decreases (increases) then the dependent variable increases (decreases).

Lower dependent variables indicate higher efficiency.

* The direction depends the dependent variable.

4. RESEARCH METHODOLOGY

This chapter presents the research methodology applied for our study. Scientific research methodology can be defined as *"a system of explicit rules and procedures that provides the foundations for conducting research and evaluating claims for knowledge." (Frankfort-Nachmias & Nachmias, 2000, p. 53)*. The research method, data collection method and data analyzing method are included in this chapter. It also gives a presentation of the data sample, the regression models and the variables used for this study.

4.1 RESEARCH METHOD

This section is a review of the two main research methods in social science; qualitative and quantitative research method, emphasizing on the quantitative approach, including arguments for using this method in our research.

The qualitative research method is explained by Frankfort-Nachmias & Nachmias (2000, p. 257) as *"an attempt to understand behavior and institutions by getting to know the persons involved and their values, rituals, beliefs, and emotions. Applying such a perspective, researchers would, for example, study poverty by immersing themselves in the life of the poor rather than collecting data with a structure interview schedule."* The qualitative research method focuses on details, nuances and the uniqueness in each respondent, with a close and transparent approach. Strategies for qualitative data collection could be interviews, field research, observations, or collection of secondary data prepared by others (Jacobsen, 2005).

With a quantitative research approach the researcher wants to collect a representative sample in order to be able to generalize from the respondents to anything that he or she is interested in commenting on. This means that the quantitative research method, because of the larger sample of respondents, usually has a higher external validity then the qualitative research method (Jacobsen, 2005). The quantitative researcher often has a good pre- knowledge of the investigated subject, and the issues are relatively clear. But the researcher wants to find out more about the frequency or extent of the phenomenon, or how often the phenomenon occurs (Jacobsen, 2005). We can turn around the earlier example from Frankfort-Nachmias & Nachmias (2000) and say that a researcher who is using a quantitative method to study poverty would collect data with a structured interview schedule rather than immersing in the poor people's lives. The quantitative research method focuses on standardized and systematic information, easier computer processing, easier structure of the information, and testing of theories and hypothesis. Strategies for quantitative data collection could be phone interviews, standardized questionnaires, standardized interviews, or collection of secondary data such as document studies and statistics (Jacobsen, 2005).

Our review of the microfinance, bank and efficiency literatures and theories has found that there is a good pre-knowledge about efficiency and problems with inefficiency in MFIs. The information is out there, defined and measurable. However, few studies are larger global studies actually testing whether the efficiency drivers, as claimed by the literatures, have a significant effect on the overall efficiency of MFIs. In order to get valid results, we need a relatively large sample size. Since we are going to study the relationship between overall efficiency measures and efficiency drivers, we find quantitative research, or more precisely econometrics, to be the best method (Greene, 2003; Ledgerwood, 1998; Studenmund, 2006; Zikmund, 2000).

4.2 Data collection Method

For our study we are using secondary data from a dataset compiled by Mersland (Roy Mersland, 2009a). The dataset have previously been used in Mersland and Strøm (2008a), Mersland and Strøm (2008b), and Mersland and Hartarska(Forthcoming) , as well as in several working papers. The dataset contains 141 variables from 379 MFIs in 74 countries. The data has been collected from risk assessments reports made by five rating agencies officially approved by C-GAP: Microrate, Microfinanza, Planet rating Crisil and M-Cril. The reports range from 10 to more than 40 pages of narrative and accounting information. Most of them report information from more than one financial year, between year 1998 and year 2008. All the numbers in the dataset have been annualized and dollarized using official exchange rates at the given time (Roy Mersland, 2009a).

When using secondary data it is important to be aware of the sources credibility and accuracy(Jacobsen, 2005). In our case we can argument that our sources are of good quality: The risk assessments reports are made by official rating agencies approved by C-GAP, and the reports are analyzed and registered in the dataset by trained and experienced persons, and again controlled by a second person.

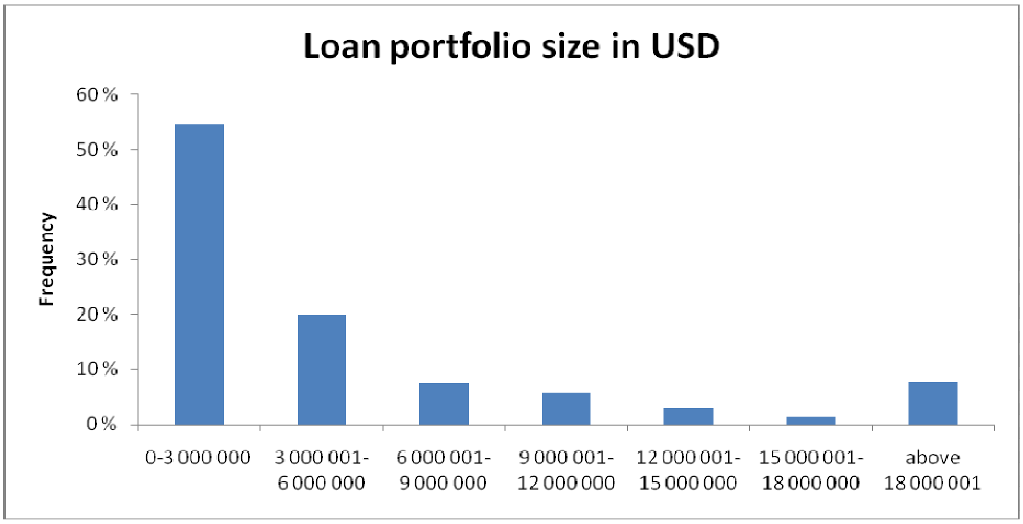
4.3 SAMPLE

Two MFIs (case 106 and 78) were excluded from the analysis due to the lack of relevant data. The total sample used for this study consists of 377 MFIs. The last year of registered data from each MFI were used in the analysis, defined as year 0. We also performed a robust check with data from the previous year (year -1). Since all of the observations are from the same point in time and represent different individual economic entities from the same time, the dataset is called cross-sectional (Studenmund, 2006)

The dataset only contains data from MFIs that voluntarily have agreed to open their accounts for scrutiny and rating, and accepted that the reports become public available (Roy Mersland, 2009a). It is important to be aware of possible differences between the rated and the non rated MFIs. Mersland and Strøm (2008b) suggest that the data is skewed towards the better performing MFIs, with the advantage that very small MFIs without the intention to apply microfinance in a business-like manner are filtered out. At the same time large firm bias is less than in alternative data sources like Mixmarket (www.mixmarket.org), since not all the mega-sized MFIs are represented.

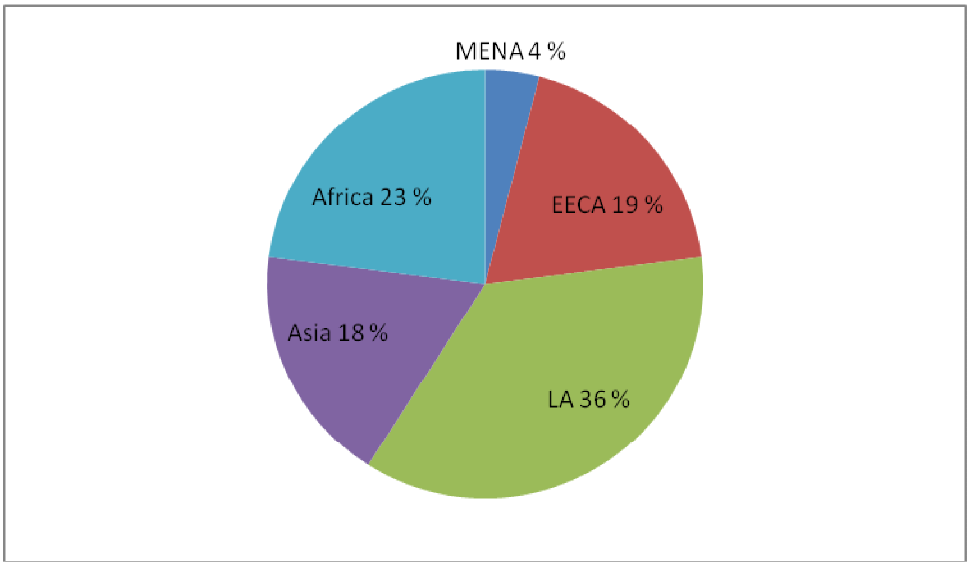
Total accumulated portfolio size for the 377 MFIs is more than 2 billion USD (2 066 574 245 USD). 75 percent of the MFIs have a portfolio size below 6 million USD, and 25 percent of the MFIs have a portfolio size ranging from 6 million USD and up to nearly 60 million USD (59 731 394). A few large loan portfolios brings the MFIs average loan portfolio size close up to 5.5 million USD (5 481 629 USD). Figure 4.1 presents the loan portfolio size on the x-axis, and the share of total MFIs in percent on the y-axis. As can be seen from the figure, 55 percent of the 377 MFIs have a loan portfolio size less than 3 million USD.

Figure 4-1: MFIs sorted by loan portfolio size



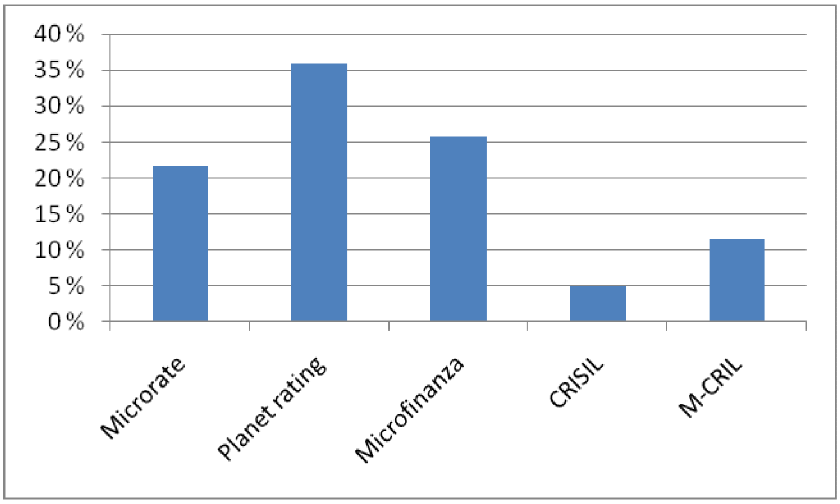
The dataset covers a broad share of the "developing" world with MFIs from 74 different countries, and over 8 million clients served during the sample period. Some countries are more represented than others, like India with 31 and Peru with 28 of the 377 MFIs. In figure 4.2 the MFIs are sorted into five regions. Asia, Africa and Eastern Europe (EECA) have a reasonably share, with respectively 66, 86 and 71 of the MFIs. Latin America (LA) has a major share with 139 MFIs, and Middle East and North Africa (MENA) has a minor share with 15 MFIs.

Figure 4-2: MFIs sorted by regions



The dataset contains data from risk assessments reports (also named rating reports) from five rating agencies. Figure 4.3 shows that the rating agencies are not equally represented in the dataset. CRISIL and M-CRIL have a minor share with 19 and 44 ratings. All of CRISILs MFI ratings, except two, are from India. The other agencies cover a wider scope globally, Microrate with 82, Planet rating with 136, and Microfinanza with 98 rating reports.

Figure 4-3: MFIs sorted by rating agencies



4.4 Model presentation

Multiple regression analyses were applied in order to identify the efficiency driver's effect on the MFIs overall efficiency. It is called multiple regressions since we are dealing with multiple independent variables. Regression analysis is explained by Studenmund (2006, p. 6):

"Regression analyses are used to make quantitative estimates of economic relationships that previously have been completely theoretical in nature. Regression analysis is a statistical technique that attempts to explain movements in one variable, the dependent variable, as a function of movements in a set of other variables, called the independent variable, through the quantification of a single equation."

There are several different regression analysis techniques, but we have chosen the ordinary least squared (OLS) estimation which is the most used one. If the classical assumptions hold then OLS estimation technique is the best available (Greene, 2003; Studenmund, 2006). Later in the analysis we will test if the assumptions hold for our models. If not, adjustments have to be made. The classical assumptions state that (Studenmund, 2006, p. 89):

I. The regression model is linear, is correctly specified, and has an additive error term

II. The error term ($\varepsilon = Y_i - E(Y_i | X_i)$) has a zero population mean.

III. All explanatory variables are uncorrelated with the error term

IV. Observations of the error term are uncorrelated with each other (no serial correlation)

V. The error terms has a constant variance (no heteroskedasticity)

VI. No explanatory variable is a perfect linear function of any other explanatory variable(s) (no perfect multicollinearity)

VII. The error term is normally distributed

The error term $\varepsilon = Y_i - E(Y_i | X_i)$, were Y_i is the observed value of the dependent variable i, and $E(Y_i | X_i)$ is the expected value of Y. The error term can never be observed, but the residuals $e_i = Y_i - \hat{Y}$, were Y_i is the ith observed value, and $\hat{Y}$ is the estimated value of the dependent variable, can be thought of as an estimate of the error term.

The general multivariate regression model with K independent variables can be represented by (Studenmund, 2006, p. 41):

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_k X_{ki} + \varepsilon_i \qquad (i = 1, 2, ..., n)$$

Where Y_i is the ith observation of the dependent variable, $X_{1i}, ..., X_{ki}$ are the ith observation of the independent variables, $\beta_0, ..., \beta_k$ are the regression coefficients, ε_i is the ith observation of the stochastic error term, and n is the number of observations. Y is an n x 1 vector of observations; X is an n x k+1 vector contains k explanatory variables for the ith firm. β is a k+1 x 1 vector of the parameters, and ε is a n x 1 vector of disturbance.

The following three models were used to identify the efficiency driver's effect on the MFIs overall efficiency. Operational expense to portfolio ratio, operating expense to assets ratio and operating expense per credit client were used as dependent variables, and 13 variables which are listed in the summary below in table XX were used as explanatory variables. The empirical multivariate regression models with 13 independent variables can be represented by:

<u>Operational cost to portfolio</u>

$$OEP_i = \beta_0 + \beta_1 \text{COProd}_i + \beta_2 \text{MC}_i + \beta_3 \text{PureFS}_i + \beta_4 \text{Age}_i + \beta_5 \text{VB}_i + \beta_6 \text{SG}_i + \beta_7 \text{Urban}_i$$
$$+ \beta_8 \text{Rural}_i + \beta_9 \text{CE}_i + \beta_{10} \text{LOA}_i + \beta_{11} \text{CO}_i + \beta_{12} \text{PerP}_i + \beta_{13} \text{Size}_i + \beta_{14} \text{HDI}_i + \beta_{15} \text{MENA}_i \quad (1)$$
$$+ \beta_{16} \text{EECA}_i + \beta_{17} \text{LA}_i + \beta_{18} \text{Asia}_i + \varepsilon_i$$

<u>Operational cost to assets</u>

$$OEA_i = \beta_0 + \beta_1 \text{COProd}_i + \beta_2 \text{MC}_i + \beta_3 \text{PureFS}_i + \beta_4 \text{Age}_i + \beta_5 \text{VB}_i + \beta_6 \text{SG}_i + \beta_7 \text{Urban}_i$$
$$+ \beta_8 \text{Rural}_i + \beta_9 \text{CE}_i + \beta_{10} \text{LOA}_i + \beta_{11} \text{CO}_i + \beta_{12} \text{PerP}_i + \beta_{13} \text{Size}_i + \beta_{14} \text{HDI}_i + \beta_{15} \text{MENA}_i \quad (2)$$
$$+ \beta_{16} \text{EECA}_i + \beta_{17} \text{LA}_i + \beta_{18} \text{Asia}_i + \varepsilon_i$$

<u>Cost per credit client</u>

$$CC_i = \beta_0 + \beta_1 \text{COProd}_i + \beta_2 \text{MC}_i + \beta_3 \text{PureFS}_i + \beta_4 \text{Age}_i + \beta_5 \text{VB}_i + \beta_6 \text{SG}_i + \beta_7 \text{Urban}_i$$
$$+ \beta_8 \text{Rural}_i + \beta_9 \text{CE}_i + \beta_{10} \text{LOA}_i + \beta_{11} \text{CO}_i + \beta_{12} \text{PerP}_i + \beta_{13} \text{Size}_i + \beta_{14} \text{HDI}_i + \beta_{15} \text{MENA}_i \quad (3)$$
$$+ \beta_{16} \text{EECA}_i + \beta_{17} \text{LA}_i + \beta_{18} \text{Asia}_i + \varepsilon_i$$

$i \in \{1, 2, ..., \text{n}\}$

The above stated models test the following hypotheses:

$\text{H}_0 : \beta_i = 0$	$\text{H}_0 : \beta_i > 0$	$\text{H}_0 : \beta_i < 0$
$\text{H}_\text{A} : \beta_i \neq 0$	$\text{H}_\text{A} : \beta_i \leq 0$	$\text{H}_\text{A} : \beta_i \geq 0$
$i \in \{1, 2, ..., 18\}$	$i \in \{1, 2, ..., 18\}$	$i \in \{1, 2, ..., 18\}$

.

4.5 Data analyzing tools

SPSS and STATA were used to analyze the data. Both are well known statistical programs and reliable tools for analyzing quantitative data. Most of the statistical work was carried out in SPSS. STATA was mainly applied for the robust regression models, and the White's test for heteroskedasticity(Hamilton, 2009).

5. DATA ANALYSES AND FINDINGS

This chapter presents the data analyses and findings carried out to determine the efficiency driver's effect on the overall efficiency of MFIs. The chapter includes regression diagnostics, descriptive statistics and regression results.

5.1 REGRESSION DIAGNOSTICS

In order to interpret the results from our models in a meaningful way, we need to test if the models are robust. Certain assumptions have to be fulfilled and special observations have to be examined. Regression diagnostics was carried out with and without the control variables included in the models. The diagnostics presented below are with control variables included in the models.

Unusual and influential data

The first stage is to check for unusual and influential data. Such data is called outliers and are recognized as observations that deviate substantially from the main trend in the relationship between independent and dependent variables. Such observations have large residuals (Christophersen, 2006).

Residuals $e_i = Y_i - \hat{Y}$, where Y_i is the observed value of the dependent variable i, and $\hat{Y}$ is the estimated value of the dependent variable (Greene, 2003; Studenmund, 2006).

A data is influential if its omission changes the regression results substantially. Such devises can affect the calculations of the parameters, the standard errors, the determination coefficient (R^2) and the test observers (Eikemo & Clausen, 2007). Identifying an outlier is not a justification for dropping that observation from the sample. A regression needs to be able to explain all the observations in a sample, not just the well-behaved ones (Studenmund, 2006). Three different methods for identifying unusual and influential data are presented in (Eikemo & Clausen, 2007):

- Leverage identifies strange combinations of values for different variables.
- DfBetas identifies each observation's influence on each variable.

- Cook`s D identifies the observations impact on the entire model

Diagnostics rule of thumbs are stated in table 5-1 (Eikemo & Clausen, 2007).

Table 5-1: Critical values for unusual and influential data

	Critical values	
	General	**Models**
Leverage	$> 2k / n$	>0,145
DfBetas	$> 2 / \sqrt{n}$	>0,124
Cook`s D	$> 4 / n$	>0,015
k-number of predictors		
n-number of observations		

First we got a OEP ratio model with a maximum leverage value of 0,843 (similar for all models), and a maximum Cook`s D value of 4.632 (similar for all models). Case 142, 158, 289, 300, 316, 342 and 349 was clearly standing out as outliers, all of them with high Leverage and/or Cooks`s D values. We found that the average outstanding loan size (LOA) in case 142 was 24 589 USD, almost twice as the case with the second largest LOA. Case 316 and 158 had an extremely high OEP ratio (1,497 and 1,393) and case 289 had a high OEA ratio (0,8949). The maximum value of the CC variable (case 300) was much larger then the second largest value, with 1329 USD for the maximum value compared to 526 USD for the second largest value. Case 342 and 336 had a large Cook`s D value in the CC model. Case 350 and 59 were also detected as outliers, but not as influential as he others. We also did the DfBetas test on the models and found only cases below the critical value, ranging from -0,07 to 0,08. All of the outliers appear to be valid observations. Still, they have a large impact on the model, and we decided to exclude case 142, 158, 289, 300, 316, 342 and 349 from the sample, additionally to the two cases (106 and 78) that were excluded from the analysis earlier due to lack of relevant data. All other cases were included in the further analysis. The maximum leverage and Cook`s D value decreased substantially when those cases where removed., down to 0,230 and 0,049 for the OEP ratio model, 0,233 and 0,154 for the OEA ratio model and respectively 0,224 and 0,113 for the CC model.

Testing the model assumptions

One of the most important jobs in regression analysis is to decide whether the classical assumptions (stated above) hold for a particular equation. If the classical assumptions hold, then the OLS estimation technique is the best available. Otherwise, adjustments should be made to OLS that take account of the particular assumptions that are not met (Studenmund, 2006).

Our regression models used for this study are stated above, and concur with the first assumption. The error term in our models has, as can be seen in table 5-2, a zero population mean. Assumption number one and two hold for our models

Table 5-2: Descriptive statics for the model residuals

Model\Residuals	Minimum	Maximum	Mean	Std. Deviation	N
OEP ratio model	-0,2487393	0,4027359	0,0000000	0,1209445	249
OEA ratio model	-0,1770110	0,3164828	0,0000000	0,0767118	248
CC model	-139,759	202,920	0,0000000	55,219	247

All explanatory variables have been checked to be uncorrelated with the error term. The Pearson correlation coefficient equals zero for all correlations, and the p-value (Sig. (2-tailed)) is 1.000 for all correlations, meaning that the probability of significant correlation is zero. The third assumption holds for our models.

Serial correlation (or auto correlation) implies correlation between values from the same variable. Auto Correlation leads to larger variance and larger standard errors for the estimates. Auto Correlation can be examined using the Durbin-Watson test. Auto correlation is not a problem since the Durbin Watson values are close to 2,0 for all models. The CC model indicates a slightly positive serial correlation (1,661), but it is still reassuringly above the critical values presented in table 5-3 (Eikemo & Clausen, 2007). Assumption number four holds for our model.

Table 5-3: Serial correlation

	Critical values	OEP ratio model	OEA ratio model	CC model

Durbin-Watson value	<1,0 or >3,0	1,852	1,934	1,661

Heteroskedasticity implies that the error terms in the model do not have a constant variance. A model with heteroskedasticity makes the hypothesis testing unreliable. It also generates inaccurate estimates for some predicted values of Y, and has negative effects on the t-tests and F-tests (Eikemo & Clausen, 2007; Studenmund, 2006). The assumption about constant variance on error terms is likely to be violated when using cross-sectional dataset similar to our dataset (Studenmund, 2006).We can test if the heteroskedasticity is significant, by performing a Whites test for heteroskedasticity. The test results are presented in Table 5-4. All models have a p-value below 10% or 5% level, which indicates heteroskedasticity in all models (Eikemo & Clausen, 2007; Greene, 2003).

Table 5-4: Heteroskedasticity in the OLS models

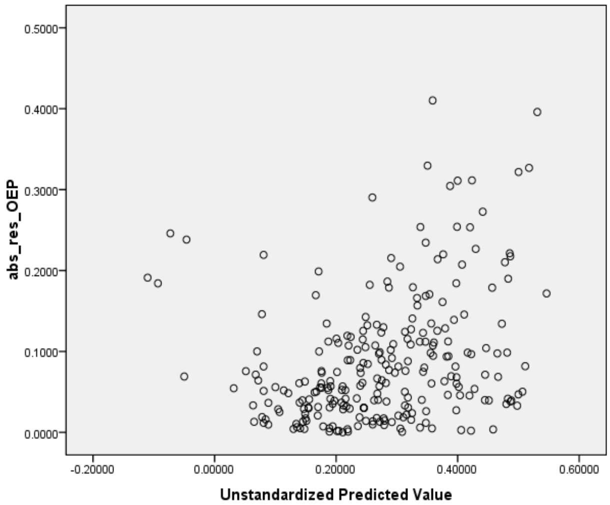
OLS Model	p-value	Significant heteroskedasticity
OEP ratio	0,0538*	Yes
OEA ratio	0,0277**	Yes
CC	0,0910*	Yes

**Significant at 5%level

*Significant at 10% level

Figure 5-1 illustrates the variation in the residuals for the OEP ratio model (Figures from OEA ratio and CC model are not reported). The residual values are presented in the Y-axis and the predicted values are presented in the X-axis. The results read out from the figures matches the Whites test results. The OEP ratio model and the OEA ratio have a clear increase in the variance of the residuals when the predicted value increases. It is the same tendencies of unequal variation of the residuals for the CC model, but not as evidently as the other models. Assumption number five is violated for our models, so adjustments have to be made.

Figure 5-1: Variance of the residuals for the OEP ratio model



The most common technique for solving the problem of heteroskedasticity is the Weighted Least-squares (WLS) regression. The WLS regression uses a proportionality factor to minimize the influence of units with large residual and maximize the influence of units with small residuals (Eikemo & Clausen, 2007; Studenmund, 2006). The general Weighted least square model can be represented by (Studenmund, 2006, p. 364):

$$Y_i / Z_i = 1/Z_i + \beta_1 X_{1i} / Z_i + \beta_2 X_{2i} / Z_i + ... + \beta_k X_{ki} / Z_i + u_i \qquad (i = 1, 2, ..., n)$$

Where Y_i is the ith observation of the dependent variable, Z_i is the ith proportionality factor, $X_{1i}, ..., X_{ki}$ are the ith observation of the independent variables, $\beta_0, ..., \beta_k$ are the regression coefficients, u_i is the ith observation of the stochastic error term, and n is the number of observations.

We computed new weighted variables, using the weighted technique explained in Eikemo & Clausen (2007). First we squared the residuals from the OLS regressions. Second, we performed OLS regression with the squared root of the residuals as the dependent variable, and retaining the independent variables from the OLS regressions. Third, we ordered predicted and absolute (positive) values of the dependent variables. Finally we squared the predicted and absolute values, getting the proportionality factors Z_i.

The WLS regressions are presented later in this chapter in table XX, and compared to the OLS regression models. We also did a Whites test for heteroskedasticity for the WLS regression models and the results are presented in table 5-5. A much higher p-value indicates no significant heteroskedasticity in our WLS regression models.

Table 5-5: Heteroskedasticity in the WLS models

WLS Model	p-value	Significant heteroskedasticity
OEP ratio	0,4293	No
OEA ratio	0,1206	No
CC	0,1366	No

**Significant at 5%level

*Significant at 10% level

Multicollinearity (and collinearity) is the correlation between independent variables. If the multi collinearity is strong, it becomes difficult to separate the variables effects from each other. Moreover, the estimates are inaccurate and has larger significant values (Christophersen, 2006). In order to identify multicollinearity, Pearson's r coefficient, tolerance (Tol) and variance inflation (VIF) was applied. Pearson's r coefficient varies between -1 and +1, and indicates the strength of the correlation. Positive correlation means that high values of X go together with high values of Y, and vice versa with negative values (Eikemo & Clausen, 2007). VIF indicates how much the variance of the regression coefficient $\hat{b}$ increases from the correlation $R_u = 0$ to the observed correlation R_u (Christophersen, 2006). Diagnostics rule of thumbs are stated in table 5-6 (Eikemo & Clausen, 2007) and (Christophersen, 2006).

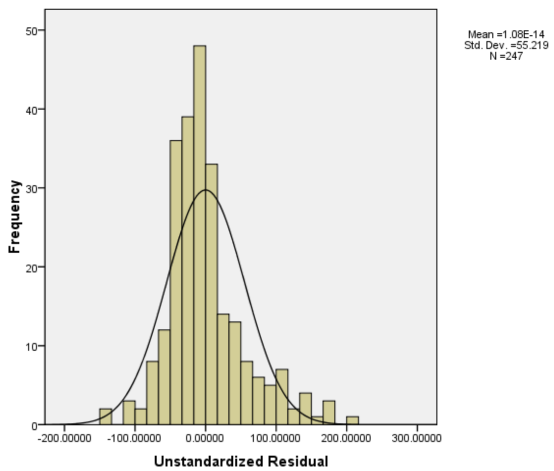
Table 5-6: Critical values for detecting multicollinearity

	Critical values
Pearson`s r	>0,8
Tol	$(1-R_u^2)<0,2$
VIF	$1/(1-R_u^2)>5$

The Pearson`s r coefficients for all relationships between the independent variables have been checked against the critical values. Some of the variables have significant correlation, but not enough to largely impact on the models. All of the correlations are reassuringly below the critical value. Most of the largest correlations can be explained by the dummy coding technique. If individual lending is stated as the main loan methodology then it cannot be solidarity group lending and vice versa. Loan outstanding average has a moderate and positive correlation with individual lending (0,538). This correlation is well known in the industry and can be explained by wealthier clients who do not prefer group lending. In other words, individual lenders are often wealthier and lend more money than group lenders (Cull, et al., 2007)

The last assumption that has to be fulfilled is the assumption about normal distributed residuals. If the residuals have a strong deviation from normal distribution it will affect the t and F-tests reliabilities(Greene, 2003; Studenmund, 2006). However, according to the central limit theorem; deviations impact on the substantial interpretation gets smaller when the sample gets larger (Studenmund, 2006). The large amount of samples collected for this study should argue that deviation from normal distribution does not have a large impact on the interpretation of the results. We used residual plot, skewness and kurtosis, and Kolmogorov-Smirnov test to identify deviation from normal distribution. The distributions of the residuals for the OEA ratio regressions are presented in figure 5-2 (OEP ratio and CC model not reported. All of distributions tend towards normal distribution, but they are left-leaned and sharper.

Figure 5-2: Distribution of the residuals from the OEA ratio model



We also looked at the skewness and kurtosis which indicates whether the distributions are warped or symmetric (Christophersen, 2006). The skewness and kurtosis for our models are presented in table 5-7. All models have small to moderate skewness and a moderate kurtosis, which indicates sharp and left-leaning distributed residuals. The same results were found in the figures.

Table 5-7: Skewness and kurtosis of the residuals

OEP ratio model		OEA ratio model		CC model	
Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
0,917	1,126	0,915	1,938	1,006	1,700

Finally, we used the Kolmogorov-Smirnov test to get a "yes or no" answer regarding the normal distribution. If the p-value is less then 0,05 then the assumption about normality of the residuals must be discarded (Gripsrud, Olsson, & Silkoset, 2004). The results from the KS test are presented in table 5-8. As can be seen in the table, the low p-values for all models reject the assumption about normal distribution. Assumption number seven is not fulfilled for the initial OLS regression models.

Table 5-8: Kolmogorov-Smirnov test for the OLS models

Critical value	OEP ratio model	OEA ratio model	CC model
Reject p<0,05	0,007	0,019	0,001

To deal with the normality problem we did a power transformation of the dependent variables as recommended in Eikemo & Clausen (2007). We decided to use a exponential factor of 0,2 in order to approach normal distributions. The following dependent variables were computed:

$OEP_i^{0,2}$

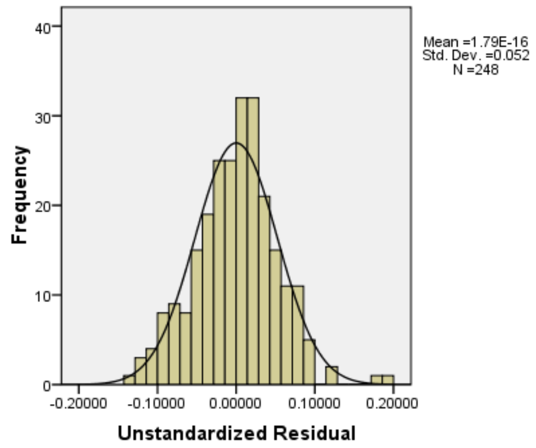
$OEA_i^{0,2}$

$CC_i^{0,2}$

were $i = 1, 2, \ldots, n$

Regression analyses were performed, using the transformed variables as dependent variables and keeping the independent variables from the initial OLS regression model. The regression results are presented later in table XX, and compared to the other results. Figure 5-2 contains the residuals from the "transformed" OEA regression (OEP ratio and CC regression not reported), and large improvement can be seen.

Figure 5-3: Distribution of the residuals from the transformed OEA ratio model



As can be seen in table 5-9, the skewness and kurtosis are much improved for all models. Only small skewness and kurtosis can be found for all models.

Table 5-9: Skewness and kurtosis of the residuals from the transformed models

$OEP_i^{0,2}$ **ratio model**		$OEA_i^{0,2}$ **ratio model**		$CC_i^{0,2}$ **model**	
Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
0,200	0,301	0,082	0,616	0,465	0,733

Also the Kolmogorov-Smirnov test show satisfying test results. The large p-value presented in table XX gives no reason to reject the assumption about normal distribution in the "transformed" models.

Table 5-10: Kolmogorov-Smirnov test for the transformed models

Critical value	$OEP_i^{0,2}$ **ratio model**	$OEA_i^{0,2}$ **ratio model**	$CC_i^{0,2}$ **model**
Reject p<0,05	0,263	0,588	0,154

Diagnostics summary

7 of the 377 cases were excluded from the sample as unusual and influential data. WLS regression analysis was carried out to deal with problems of heteroskedasticity in the initial OLS model. The WLS regression models are presented in table 5-16. We removed the HDI variable from our models because of strong multicollinearity. Our initial OLS model did not fulfil the normality assumption, so our dependent variables were transformed to meet the normality assumption. The transformed models are presented in table 5-17.

5.2 Descriptive statistics

Table 5-11 presents the descriptive statistics from both the dependent variables and the explanatory variables. These statistics were presented after unusual and influential data were removed.

Table 5-11: Descriptive statistics for the dependent and independent variables

Variable	N	Minimum	Maximum	Mean	Std. Deviation
OEP ratio	370	0,0191	1,0830	0,267572	0,1725148
$OEP^{0,2}$	370	0,45311	1,01607	0,7443061	0,09638761
OEA ratio	366	0,0194	0,7241	0,194697	0,1146146
$OEA^{0,2}$	366	0,45453	0,93748	0,7023952	0,08174192
CC	366	1	1329	118,45	123,995
$CC^{0,2}$	366	1,07199	3,50099	2,3960716	0,50807519
COProd	330	7	1456	297,34	215,078
MC	346	1	7	3,90	1,5401
PureFS	369	0	1	0,82	0,388
Age	369	1	79	10,47	7,476
VB	345	0	1	0,21	0,405
SG	345	0	1	0,28	0,447
IL	345	0	1	0,52	0,500
Urban	359	0	1	0,31	0,462
Rural	359	0	1	0,27	0,445
UaR	359	0	1	0,42	0,495
CE	329	0	21053	5907,19	4158,067
LOA	363	15	6754	698,59	857,064
CO	329	0,07	0,92	0,4682	0,15934
PerP	360	0	1	0,55	0,498

Size	370	11,693	18,784	15,03628	1,260892
Assets	370	119705	143811137	7635566	13891569
HDI	370	0,361	0,863	0,66481	0,131533
MENA	370	0	1	0,04	0,197
EECA	370	0	1	0,18	0,387
LA	370	0	1	0,37	0,484
Asia	370	0	1	0,18	0,383
Africa	370	0	1	0,23	0,419
Valid N (OEP ratio model)	249				
Valid N (OEA ratio model)	248				
Valid N (CC model)	247				

All of the variables have a solid sample size with a share of missing data ranging from 0 to 12 percents. Cost per employee (CE) and credit officer ratio (CO) have the most missing values. The valid sample size used in our regression analysis is respectively 249 for the OEP ratio model, 248 for the OEA ratio model, and 247 for the CC model.

Operating expense to portfolio ratio and operating expense to asset ratio

The mean value of the OEP ratio (0, 267572) indicates that the MFIs operating expenses are approximately 27 percent of the average outstanding loan portfolio, and the mean OEA ratio (0,194697) indicates that the operating expenses are approximately 19 percent of the total assets. Microbanking bulletin reported from a benchmark of 890 MFIs, an average OEA ratio of 14 percent and an average OEP ratio of 19,2 percent in 2007 (MIX, 2008). The ratios indicate highly inefficiency compared to commercial banks. The average general and administrative (G&A) expense to assets ratio from major banks in the US was 2,87 to 3,08 percent over the years 2002-2006 (McCune, 2007). Only 11 of the 371 MFIs from our sample had an OEA ratio below 5 percent. 140 of 371 MFIs had an OEA ratio below 14 percent, and 150 of 371 MFIs had an OEP ratio below 19,2 percent. The maximum OEP ratio (1,0830) bring forth one MFI with operating expenses larger than the total average outstanding portfolio. It is not efficient at all and neither sustainable. Figure 5-4 illustrates the distribution of the OEP ratio and the transformed OEP ratio. Figure 5-5 illustrates the distribution of the OEA ratio and the transformed OEA ratio

Figure 5-4: Frequency of the OEP ratios and the transformed OEP ratios

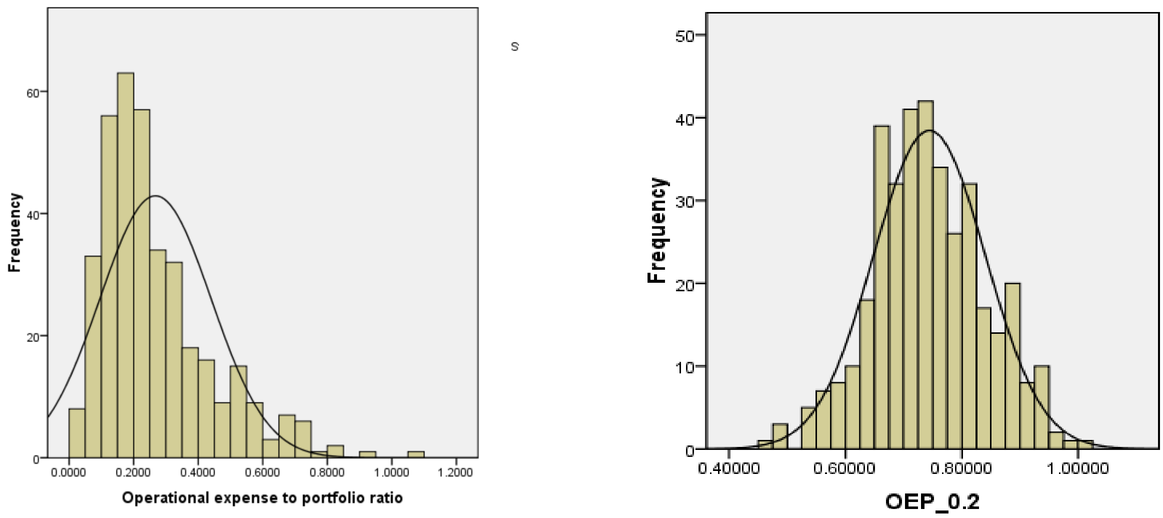
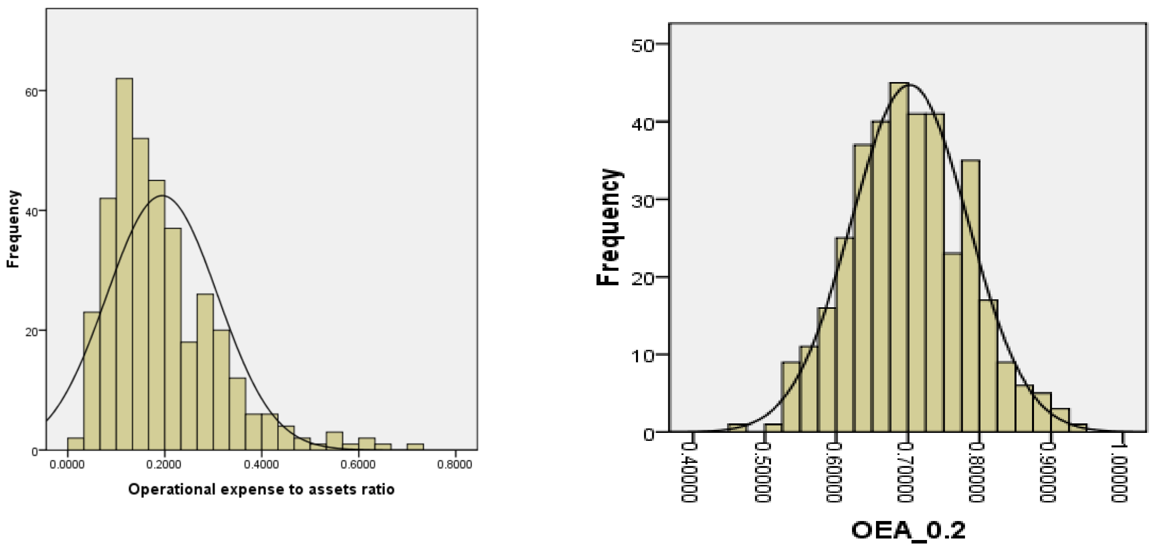


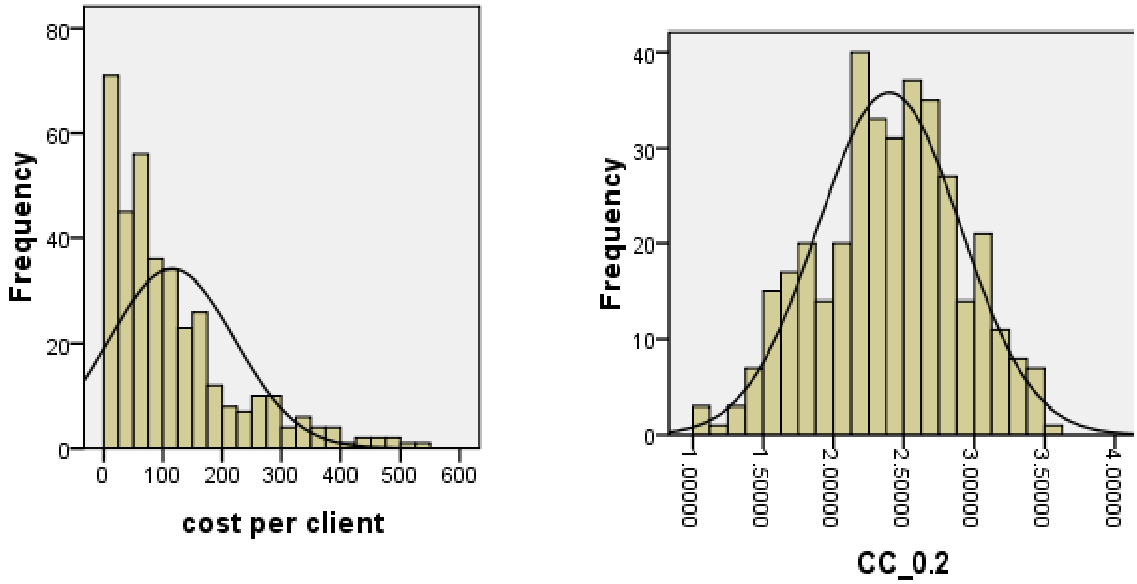
Figure 5-5: Frequency of the OEA ratio and the transformed OEA ratio



<u>Cost per client</u>

The mean value of the CC variable (118,45 USD) indicates that one credit client costs approximately 118 USD per year, not considering the purchasing power in each country. However, the minimum values, starting from 1 USD, should indicate effective MFIs regardless of purchasing power. Microbanking bulletin reported from their benchmark an average cost per credit client (or cost per borrower) of 117 USD (MIX, 2008), which is similar to our findings. 207 of the 373 MFIs from our sample had cost per credit client less than 100 USD. As can be seen in figure 5-6, the transformed CC variable has a distribution much closer to normal compared to the ordinary CC variable.

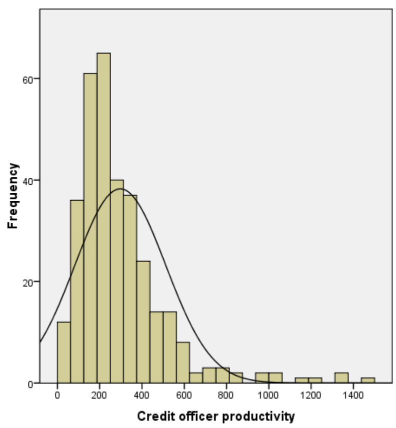
Figure 5-6: Frequency of the costs per client and the transformed cost per client



Credit officer productivity

The high standard deviation of the credit officer productivity (215,078) is an indication of a sector with a widely spread when it comes to productivity. Figure 5-7 illustrates the distribution of the MFIs credit officer productivity from our sample. It can be seen that most of the samples lie in the lower area, with 205 of the 330 MFIs with a lower then average productivity (297,34). The productivity seems to be higher compared to the Microbanking Bulletin benchmark, despite that the efficiency is lower. Microbanking bulletin reported 217 credit clients per credit officer (or borrower per loan officer) in average from their MFIs in 2007(MIX, 2008). Some of the MFIs from our sample stand out with high productivity, making the right-tailed distributions. Our sample contains 20 of 330 MFIs with credit officer productivity higher than 600 clients per credit officer.

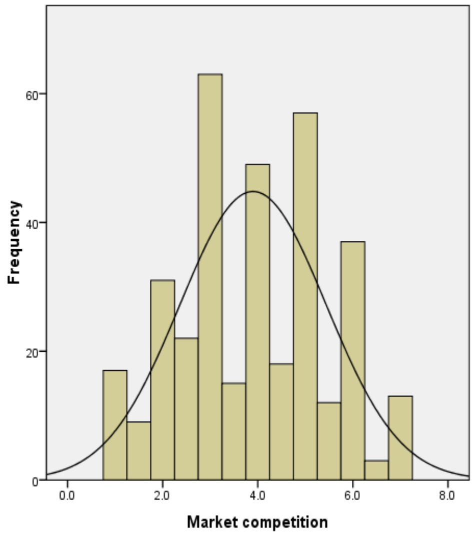
Figure 5-7: Frequency of the credit officer productivity



Market competition

As can be seen in figure 5-8, the market competition variable tends to be normally distributed. The man value (3,90) which is larger than the median value (3,5) indicates an overall competitive microfinance market. All of the "point and a half" values (for example 1,5 and 6,5) are a consequence of dissent competition estimation between the two subjective assessments.

Figure 5-8: Frequency of the market competition



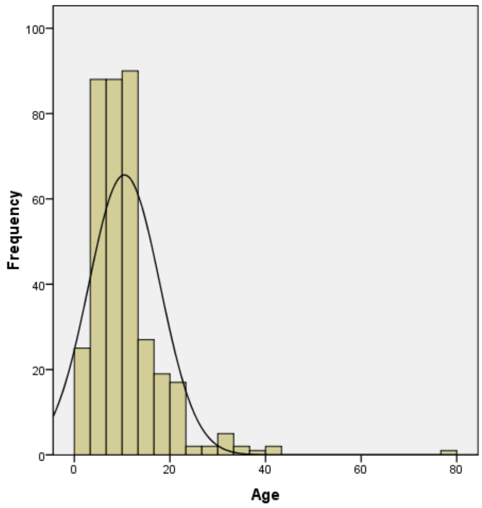
Pure financial service

According to the mean value of the Pure FS variable (0,82) are 82 percent of the MFIs specialized into only providing financial services. The remaining 18 percent of the MFIs provide additionally non-financial services such as social intermediation, enterprise development, health, nutrition, education and literacy training.

Age

The mean value of the Age variable (10,47 years) indicates that most of the MFIs are quite well settled. Our findings consents with the average age (10 years) reported in the Microbanking rapport (MIX, 2008). We only found 25 of 369 MFIs in our sample that were three years of age or younger. 125 of the 369 MFIs were between four and seven years old, and 219 of 369 MFIs were older then seven years. The oldest MFI (79 years) is almost twice the age of the second oldest (43 years). No influential impact on the regression models was found in the regression diagnostics for this particular case (case 117). The distribution of the Age variable is illustrated in figure 5-9. The distribution is right tailed.

Figure 5-9: Frequency of the MFIs age



Main loan methodology

The mean value of the VB (0,21), SG (0,28), and IL (0,52) variables indicates that individual lending is the most used lending methodology. 52 percent of the MFIs use individual lending as their main loan methodology, 21 percent use Village banking and 28 percent use solidarity group lending. Our findings consent with the Microbanking bulletin rapport (MIX, 2008).

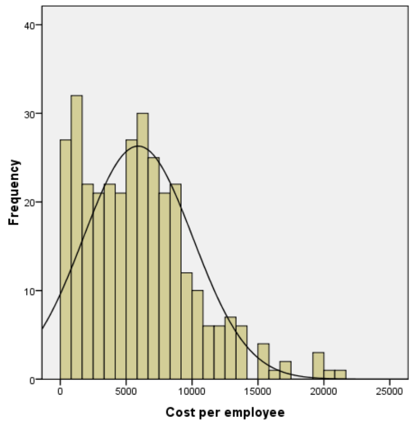
Area of intervention

The mean value of the Urban (0,31), Rural (0,27) and UaR (0,42) variables indicate that 31 percent of the MFIs are operating in Urban areas, 27 percent in rural areas and 42 percent in both urban and rural areas.

Cost per employer

There are large differences between the minimum, mean and maximum costs per employer, and the deviation is rather high. Without considering the purchasing power, our findings indicate large differences in labour cost between MFIs. The mean value of cost per employee (5907,19 USD) indicates that one employee cost approximately 5 907 USD per year. Figure 5-10 contains the distribution of cost per employee. As can be seen in the figures, the majorities of cost per employee lie between 0 and 10 000 USD.

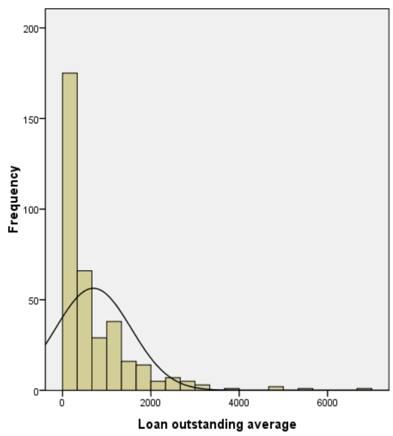
Figure 5-10: Frequency of the costs per employee



Loan outstanding average

There are also large differences between the minimum, mean and maximum loan outstanding average, and the deviation is rather high. 243 of the 363 MFIs have average outstanding loan amount lower than the mean (698,59 USD). This is high compared to the average outstanding loan amount of 505 USD reported in the Microbanking bulletin (MIX, 2008). Without considering the purchasing power, our findings indicate large differences in loan amount between MFIs. The MFIs average loan outstanding loan amount can be seen in table 5-11.

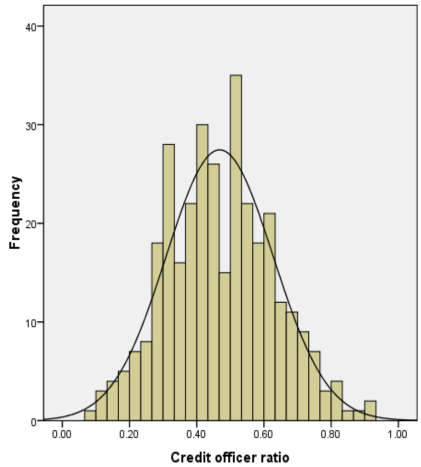
Figure 5-11: Frequency of the average outstanding loan amounts



Credit officer ratio

The credit officer ratio has to lie between zero and one. As can be seen from figure 5-15, the credit officer ratio is close to normally distributed. The mean value are almost right in the middle (0,47), and indicates that almost half of the staff are credit officers working with income generating activities. It is lower then the average value from the Microbanking bulletin report which has a credit officer ratio (or personnel allocation ratio) of 0,55 (MIX, 2008).

Figure 5-12: Frequency of the credit officer ratios



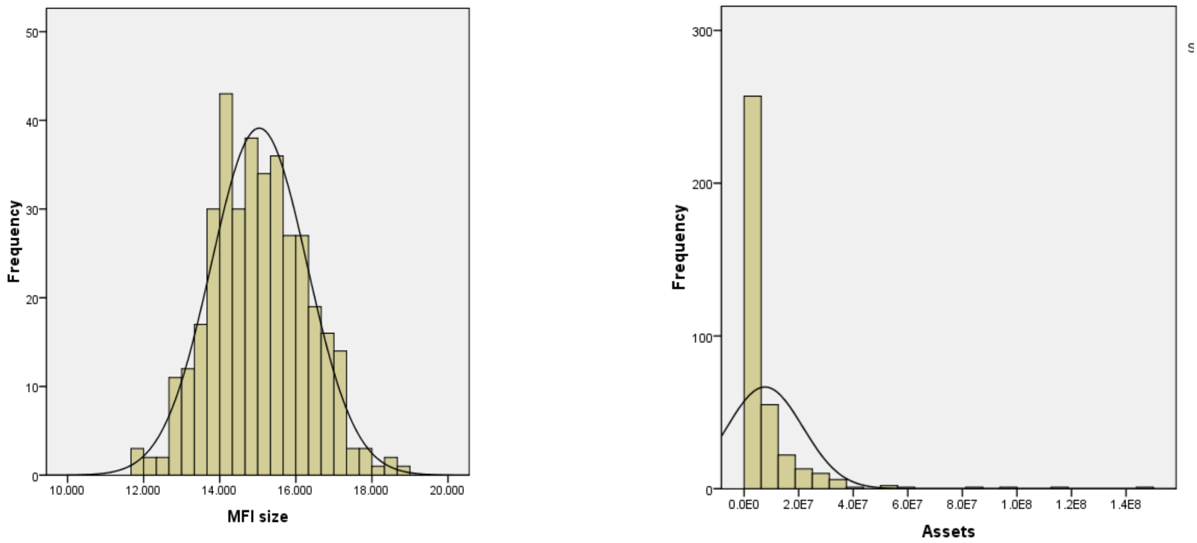
Performance pay

The PerP variables with a mean value of 0,55 indicates that 55 percent of the MFIs pay the credit officers based on their financial performance. 45 percent of the MFIs do not offer performance based pay.

MFI size

The size variable is measured by the logarithm of assets, and the motive for transforming the total assets, can be explained by comparing the figures below. Figure 5-13 illustrate the logarithm of total assets on the left and total assets on the right. The Logarithm of assets has a fine normal distribution compared to total assets who are and far from being normally distributed. There is a wide spread in the MFIs size, indicated by large differences between minimum, maximum and mean value, and standard deviation. A few of the MFIs are multimillion organizations providing financial services to hundreds of thousands of clients. Some of the other MFIs are small-scale entities who only providing financial services in the local areas. The largest MFI in our sample, (measured by size) have 143 811 137 USD in total assets serving 419 514 clients. The smallest MFI has 119 705 USD in total assets and serve 1 419 clients. The mean value is 7 635 566 USD and the standard deviation is 13 891 569 USD

Figure 5-13: Frequency of MFIs sizes and MFIs total assets



Regional control variables

Since MFIs sorted by regions are presented earlier in figure 4-2, there is not much point in presenting them again. The only change is that EECA has increased its share with one percent (from 18 to 19 percent), and LA has decreased its share with one percent (from 37 to 36 percent).

5.3 Regression results and discussion

We have earlier presented hypotheses about efficiency driver's effect on the MFIs overall efficiency. This section presents the results and the interpretation of the results from the regression analyzes, carried out to confirm or reject our hypotheses. First, we will explain the meaning of the values presented in the tables.

To decide whether to reject the null hypothesis or not, we use a critical value (or significance level) to divide the acceptance region from the rejection region. The critical value can be decided based on the weight between the consequence of rejecting a true null hypothesis, and the consequence of not rejecting a false null hypothesis. If the null hypothesis is true and we reject it, we've made a type I error. We can only reject a true null hypothesis when $\hat{\beta}$ falls in the rejection region, so a lower critical value lowers the chance on rejecting a type I error. However, decreasing the chance of a type I error means increasing the chance of not rejecting a false null hypotheses (type II error). If the critical value is set to low, then we can almost never reject true null hypotheses, whether they're true or not (Eikemo & Clausen, 2007; Studenmund, 2006). Studenmund (2006) recommend a five percent level of significance as a critical value, but also a ten percent level of significance should be considered in some cases were the consequence of type II error is large. If the level of significance is ten percent and we reject the null hypothesis at that level, then the result would have occurred only ten percent of the time that the null hypothesis was indeed correct. Both five and ten percent level of significance is pointed out in the tables presented in the next section, but we are emphasizing on the five percent level.

The marginal significance level is given in the tables, denoted as "p-value". The p-value gives you the lowest level of significance at which we could reject the null hypothesis. It ranges between 0 and 1, and a low p-value cast more doubt on the null hypothesis. A p-value of 0,10 is equal to being statistical significant at a ten percent level (Eikemo & Clausen, 2007; Greene, 2003; Studenmund, 2006). Our decision rule is stated below.

Decision rule :

If p>0,10 Reject H_0

If p<0,10 Do not reject H_0

We decided to also include the t-value because of the conventional and popular use of it. Still, we will emphasize on commenting on the p-value, which practically gives you the same answer, only in a more direct and precise way.

A multivariate regression coefficient β_K *indicates the change in the dependent variable associated with a one-unit increase in the independent variable in question; holding constant the other independent variables in the equation (Studenmund, 2006, p. 41).* Our regression coefficients determine the change in the overall efficiency with one-unit increase in one of the efficiency drivers, given that all of the other efficiency drivers are held constant. The true β_k can never be observed, but the regression analyses can estimate beta, denoted $\hat{\beta}$ as (Christophersen, 2006; Eikemo & Clausen, 2007; Studenmund, 2006).

The standard error, $SE(\hat{\beta}_k)$, is the standard deviation of the parameter $\hat{\beta}_k$. There is a probability of 68,2 percent that the true β_k lies within the values $-SE(\hat{\beta}_k)$ and $+SE(\hat{\beta}_k)$. An increase in sample size will cause standard error to fall; the larger the sample, the more precise our coefficient estimates will be. The difference between $\hat{\beta}_k$ and $SE(\hat{\beta}_k)$ determines the p-value (Eikemo & Clausen, 2007; Studenmund, 2006).

Standardized $\hat{\beta}_k$ indicates the effect on the independent variable compared to the other dependent variables. It is computed by:

$$\hat{\beta}_k \frac{\hat{S}_Y}{\hat{S}_{X_k}}$$

where $\hat{S}_Y$ is the standard deviation of the dependent variable, and $\hat{S}_{X_k}$ is the standard deviation of the independent variable. The standardized $\hat{\beta}_k$ range from -1 to 1, and a value far from zero indicates a large impact on the dependent variable $\hat{Y}$ (Christophersen, 2006; Eikemo & Clausen, 2007).

We have also performed F-tests to deal with the overall fit of the models. The F-test measures whether there is significance of having all regression coefficients equal to zero, or not. A low significance level indicates a good model fit. The following hypothesis is tested (Studenmund, 2006; Zikmund, 2000):

$$\mathrm{H_0} : \mathrm{H_A} \text{ is not true}$$
$$\mathrm{H_A} : \beta_1 = \beta_2 = \cdots = \beta_k = 0$$

While the F-test deals with the significance of the overall fit of the model, we have R^2 and adjusted R^2 to measure the degree of the overall fit. They are both ratios in the interval $0 \leq \text{(adjusted) } R^2 \leq 1$. If the value is close to zero then the model fails to explain the values Y_i better then the sample mean $\overline{Y}$. If the value is close to one, it tells us that everything effecting Y_i are explained by the independent variables in the model. In cross sectional data, like ours it is common to get low values of R^2 and adjusted R^2. One large problem with the R^2 (not the adjusted) is that adding another independent variable to the equation can never decrease it. You can be tempted to add more variables to increase R^2 but the fact is that you add a lot of noise to the model. The adjusted R^2 take this problem into consideration. By adjusting for degrees of freedom in the model, we get a better understanding of the contribution of an additional independent variable. If the adjusted R^2 decreases when another independent variable is added, it suggests that we should leave the variable out of the model (Christophersen, 2006; Eikemo & Clausen, 2007; Studenmund, 2006).

Regression model 1: Operational expense to portfolio ratio model

Table 5-12 shows the regression results using OEP ratio as the dependent variable measuring overall efficiency. The F-test indicates a good model fit, and the adjusted R^2 indicates that 47,2 percent of the OEP ratio is explained by the explanatory (independent) variables in our model.

Table 5-12: Regression results from the OEP ratio model

X_k	$\hat{\beta}$	SE($\hat{\beta}_k$)	**standardized** $\hat{\beta}_k$	**t-value**	**p-value**
(Constant)	0,86259	0,12860		6,707	0,000**
COProd	-0,00035	0,00005	-0,428	-6,995	0,000**
MC	-0,00910	0,00532	-0,082	-1,710	0,089*
PureFS	0,02216	0,02375	0,046	0,933	0,352
Age	-0,00206	0,00139	-0,077	-1,486	0,139
VB	0,15288	0,02932	0,312	5,214	0,000**
SG	0,08891	0,02348	0,224	3,787	0,000**
Urban	0,04365	0,01956	0,123	2,231	0,027**
Rural	0,01436	0,02410	0,032	0,596	0,552
CE	0,00001	0,00000	0,271	4,420	0,000**
LOA	-0,00010	0,00002	-0,451	-6,654	0,000**
CO	-0,17720	0,07063	-0,152	-2,509	0,013**
PerP	-0,00744	0,01801	-0,021	-0,413	0,680
Size	-0,02449	0,00826	-0,167	-2,964	0,003**
MENA	-0,11471	0,04720	-0,148	-2,430	0,016**
EECA	-0,09829	0,03130	-0,244	-3,140	0,002**
LA	-0,04431	0,02680	-0,129	-1,654	0,100*
Asia	-0,12167	0,03788	-0,183	-3,212	0,002**

Dependent variable: OEP ratio

R^2 : 0,509

adjusted R^2 : 0,472

F-test: 0,000

N: 249

**Significant at 5% level

* Significant at 10% level

We can observe that some of the independent variables are not statistical significant. Age has no significant effect on the OEP ratio, contradicting earlier findings found in for example Gonzalez (2007). Yet, we find age significant in the WLS presented in table 5-16 and the robustness check presented in table 5-18 which indicates more reasonable results. Neither did we find significant effect on the OEP ratio whether the MFIs only provide financial services or additionally provide non-financial services (p=0,352) in the initial OLS model, but we found significant effect in the WLS model. Performance pay does not have a significant effect on the OEP ratio even though Holtmann (2002) asserts that highly productive MFIs often have incentive schemes. The designs of the incentives schemes varies among MFIs and our finding suggests that MFIs incentive schemes are designed to stimulate other areas like better repayment rates or growth instead of cost-efficient operations. Market competition is only significant at a ten percent level for the OEP ratio. None of the other regression models found market competition to be significant, except for the robustness check of the CC model. These findings contradicts findings in for example Rhyne and Otero (2006) and Nickell et.al (1997). It indicates that the market competition variable, described as a rough guide to the relative competition pressure in the microfinance markets, is inadequate to measure the effect of market competition. Latin America turns out only to be significant at a ten percent level. Additionally Latin America turns out to be more cost-efficient than their African counterparts. If none of the variables have been counted for then the constant suggest an OEP ratio of 0,86259.

Credit officer productivity is very significant with a p-value lower then 0,001. In other words, there is more than a 99,9 percent chance that credit officer productivity has an effect on the MFIs overall efficiency. This is also supported by a very low standard error (0,00005) and a high t-value (-6,995). The standardized regression coefficient (-0,428) indicates a strong impact on the OEP ratio. A $\hat{\beta}$ value of -0,00035 state that the OEP ratio decreases with -0,00035 with a marginal increase in credit officer productivity, holding the other independent variables constant (ceteris paribus). For example, if one MFI with a loan portfolio of 5 500 000 USD had managed to provide one client extra for each credit officer, it is estimated that they would decrease operational cost with 1925 USD[1] per annum (p.a), ceteris paribus. Increased credit officer productivity has a significant and positive effect on the MFIs efficiency, measured by OEP ratio (decreasing). Similar results can be found in Arsyad (2005) and Luzzi and Weber (2006).

We can read out from the table that lending methodology also has highly significant effect on the OEP ratio. Village banking is the least efficient methodology compared to the other two, using OEP ratio as a measurement. MFIs providing village bank lending have an estimated 0,15288 higher OEP ratio then individual lending, and a 0,06397 higher OEP ratio then solidarity group lending, ceteris paribus. Solidarity group lending is more efficient then village banking, but less efficient then individual lending (0,08891), ceteris paribus. This implies that MFIs with village banking and solidarity group lending uses more costs to operate their portfolio compared to MFIs with individual lending. For example, if one MFI with a loan portfolio of 5 500 000 USD had changed its lending methodology from village banking to individual lending, it is estimated that they would decrease operational cost with 840 840 USD[2] p.a. Individual lending methodology has a positive effect on the MFIs efficiency, measured by OEP ratio (decreasing), compared to the other lending methodologies. Similar results can be found in Cull (2007).

We also found some significant differences in the efficiency comparing MFIs areas of intervention, with OEP ratio as an efficiency measure. MFIs working in urban areas are significantly (p=0,027) less efficient (0,04365) than MFIs working in both urban and rural areas. This suggests that urban areas are more expensive to operate in than rural areas. Lack of technology and lower population density should argument for lower efficiency in rural areas. Moreover, labour costs are lower in rural areas than in urban areas measured by the average income (Wiggins & Proctor, 2001). Since salary costs are one of the main components of operating costs, the difference in labour costs could explain the lower

[1] 5 500 000 USD*(-0,00035) = 1925 USD

[2] 5 500 000 USD*(-0,15288) = 840 840 USD

efficiency of MFIs working in urban areas compared to MFIs working rural or both urban and rural areas. We found no significant differences in the efficiency of MFIs working in rural areas versus MFIs working in both rural and urban areas (p=0,552). Urban intervention has a significant and negative effect on the MFIs efficiency, measured by OEP ratio (increasing), compared to rural intervention, and both urban and rural intervention.

Cost per employee is found to have a highly significant effect on the OEP ratio. It is one of the most significant variables in the model, with a very low p-value (>0,001), t-value (4,420), and standard error (>0,00001). It is estimated that 1 USD increase in cost per credit officer, will lead to an increase in the OEP ratio of 0,00001, ceteris paribus. Our findings suggest that MFIs will increase their efficiency by decreasing wages. This is supported by Arsyad (2005). However, this conclusion is based on keeping everything else constant, and there is reason to believe that reducing wages could lead to other negative effects. In a labour market where price on labour reflects quality of labour; we may expect worse performance and lower productivity as a consequence of reducing wages. Increasing cost per employee has a significant and negative effect on the MFIs efficiency, measured by OEP ratio (increasing).

Loan outstanding average is found to be the most influent efficiency driver, measured by OEP ratio, with a standardized regression coefficient of -0,413. We found a standard error of 0,00002, a t-value of -6,654 and a p-value of less then 0,001. A marginal increase in loan outstanding average decreases the OEP ratio with 0,00010, ceteris paribus. Our findings suggest a positive effect on the efficiency, if MFIs increase their average loan amount. In other words; it is more expensive to provide many smaller loans compared to fewer and larger loans (CGAP, 2009a). This can be explained by the transactions cost related to each loan(Hulme & Mosley, 1996). Yet, increasing the loan amount is inconsistent with reaching the poorest of the poor and outreaching more clients (R Mersland & Strøm, 2008a). Providing poor and low income people with small-scale financial services is the definitions on microfinance and the main reason why MFIs exists. Higher loan amounts exclude the poorest and favour wealthier clients, because poorer clients will not be able to service large loans. Increasing the average outstanding loan amount has a significant and positive effect on the MFIs efficiency, measured by OEP ratio (decreasing). This result complements previous findings in Cull et.al (2007) and Gonzalez (2007).Credit officer ratio is significantly affecting the OEP ratio. The negative regression coefficient (-0,177) indicates that a higher credit officer ratio will lower the OEP ratio. MFIs would obtain higher efficiency if they used more staff as credit officers. We believe that shifting from administration work into income generating activities is the main effect. Increasing the MFIs loan portfolio can be done by sending more staff out in the field reaching more clients. It is important to be aware that an administration is useful and needed. There is reason to believe that a credit officer ratio close to one will have a negative effect on the MFI, lacking important management. This negative effect is not explained by the model. Increasing the credit officer ratio has a significant and positive effect on the MFIs efficiency, measured by OEP ratio (decreasing).

We also found that size has a significant effect on the overall efficiency, using the OEP ratio as an efficiency measurement ($p<0{,}001$). A $\hat{\beta}_{13}$ value of -0,02273 indicates that a marginal increase in size reduces the OEP ratio with 0,02273, ceteris paribus. We have to interpret the results by using e^{unit} = Total assets. For example, if one MFI size has a unit size of 14 it will have e^{14} = 1 202 604 USD in total assets. If some other MFI has a unit size of 15 it will have e^{15} = 3 269 017 USD in total assets. The negative regression coefficient suggests that larger MFIs are more efficient compared to smaller MFIs (decreasing OEP ratio), ceteris paribus. Our findings coincide with the findings by Gonzalez (2007) and Munir and Ahmad (2006), confirming scale of economics. Increasing MFI size has a significant and positive effect on the MFIs efficiency, measured by OEP ratio (decreasing).

Africa is the least efficient region to operate in, comparing the five regions. The OEP ratio is 0,12167 higher for MFIs operating in Africa compared to MFIs operating in the most efficient region Asia, ceteris paribus. MFIs operating in Latin America has 0,04431, EECA has 0,09829 and MENA has 0,11471 lower OEP ratio then Africa, ceteris paribus.

<u>Regression model 2: Operational expense to assets ratio model</u>

Table 5-13 contains the regression results using OEA ratio as the dependent variable measuring overall efficiency. The F-test indicates a good model fit, and the adjusted R^2 indicates that 50 percent of the OEA ratio is explained by the explanatory (independent) variables. We did not expect too much deviation from the OEP ratio regression, and we did not find much either. It is reasonable since in average 66 percent of the assets are made up of loan portfolio. We did expect the regression coefficients in the OEA ratio model to be less negative or less positive then the regression coefficients from OEP ratio model. This expectation was confirmed for all coefficients expect for the two non-significant coefficients for the PureFS and Rural variable. We will concentrate on commenting on results that are different from the OEP regression model.

Table 5-13: Regression results from the OEA ratio model

X_k	$\hat{\beta}$	SE($\hat{\beta}_k$)	**standardized** $\hat{\beta}_k$	**t-value**	**p-value**
(Constant)	0,58092	0,08182		7,100	0,000**
COProd	-0,00020	0,00003	-0,355	-6,007	0,000**
MC	-0,00347	0,00338	-0,048	-1,027	0,306
PureFS	0,02385	0,01507	0,077	1,582	0,115
Age	-0,00068	0,00088	-0,039	-0,767	0,444
VB	0,12826	0,01862	0,403	6,889	0,000**
SG	0,06760	0,01490	0,261	4,536	0,000**
Urban	0,02833	0,01244	0,123	2,277	0,024**
Rural	0,01889	0,01538	0,065	1,228	0,221
CE	0,00001	0,00000	0,349	5,826	0,000**
LOA	-0,00006	0,00001	-0,413	-6,244	0,000**
CO	-0,11411	0,04481	-0,150	-2,546	0,012**
PerP	0,00302	0,01143	0,013	0,264	0,792
Size	-0,02273	0,00527	-0,238	-4,316	0,000**
MENA	-0,01844	0,02994	-0,037	-0,616	0,539
EECA	-0,00906	0,01987	-0,035	-0,456	0,649
LA	-0,00056	0,01702	-0,003	-0,033	0,974
Asia	-0,02554	0,02404	-0,059	-1,063	0,289

Dependent variable: OEA ratio

R^2 : 0,534

Adjusted R^2 : 0,500

F-test: 0,000

N: 248

**Significant at 5% level

* Significant at 10% level

If none of the variables have been counted for then the constant suggest a OEA ratio of 0,58092. Market competition was significant at a ten percent level in the OEP ratio model, but in the OEA ratio model has the p-value grown to 0,306. The Pure financial service variable has a much lower p-value in the OEA ratio model (0,115) compared to the OEP ratio model (0,352), yet it is not significant. The age variable has a higher p-value (0,444) and the rural variable has a lower p-value (0,221) compared to the OEP ratio model. Performance pay has a positive regression coefficient in the OEA ratio model in contrast to a negative coefficient in the OEP ratio model, but those results are unreliable due to the very high p-values. The only remarkable distinguish from this model compared to the first one, is the non-significant region variables. All of the region variables are significant in the OEP ratio model (LA at 10 % level) but not in the OEA ratio model. We find no evidence of efficiency differences when comparing regions, using OEA ratio as efficiency measurement. Our results imply that the efficiency differences evens out when we include other assets additionally to loan portfolio. Since the operating expenses are equal in the OEP and OEA ratio, this should mean that for example Africa has relatively more of additional assets compared to Asia. Beyond these comments on the OEA ratio model, there is not much to point out other then it is confirming the results from the OEP ratio model.

Regression model 3: cost per client model

Table 5-14 contains the regression results using cost per credit client as the dependent variable measuring overall efficiency. The CC variable is not a ratio, so the regression coefficients are given in USD. The F-test indicates a good model fit, and the adjusted R^2 indicates that as much as 70,4 percent of the cost per client is explained by the explanatory (independent) variables in our model. We found it very interesting that only seven of the variables, including two control variables are significant. An explanation percent of 70 percent and few significant variables indicates that MFIs can achieve more cost-efficient operations only by concentrating on a few efficiency drivers. However we found more of the variables significant in additional analysis and robustness check which can indicate that there are more variables affecting cost per client. This will be further discussed in section 5.4.

Table 5-14: Regression results from the CC model

X_k	$\hat{\beta}$	SE($\hat{\beta}_k$)	**standardized** $\hat{\beta}_k$	**t-value**	**p-value**
(Constant)	268,741	58,953		4,559	0,000**
COProd	-0,174	0,023	-0,350	-7,593	0,000**
MC	-1,814	2,435	-0,027	-,745	0,457
PureFS	10,399	10,871	0,036	0,957	0,340

Age	-1,303	0,640	-0,080	-2,036	0,043**
VB	9,550	13,577	0,032	0,703	0,483
SG	-8,242	10,749	-0,034	-,767	0,444
Urban	13,037	8,973	0,060	1,453	0,148
Rural	-12,936	11,011	-0,048	-1,175	0,241
CE	0,009	0,001	0,324	7,023	0,000**
LOA	0,066	0,007	0,487	9,529	0,000**
CO	-186,811	32,353	-0,263	-5,774	0,000**
PerP	-8,128	8,239	-0,038	-0,987	0,325
Size	-4,425	3,798	-0,049	-1,165	0,245
MENA	-24,322	21,558	-0,052	-1,128	0,260
EECA	-34,476	14,305	-0,141	-2,410	0,017**
LA	-31,599	12,253	-0,150	-2,579	0,011**
Asia	-19,564	17,300	-0,048	-1,131	0,259

Dependent variable: CC

R^2 : 0,724

Adjusted R^2 : 0,704

F-test: 0,000

N: 247

**Significant at 5% level

* Significant at 10% level

If none of the variables have been counted for then the constant suggest a cost per client of 268,741 USD. Credit officer productivity is, like we found in the other models, very significant (p<0,001). It also has a large effect on the cost per client (standardized $\hat{\beta}$ = -0,350). Market competition has no significant effect on cost per client. This fortifies our discussion made earlier about market competition. We found age to significantly effecting cost per client, which is different from what we found in the other two regression models. Our findings imply that mature MFIs compared to younger MFIs increase credit clients relative to operational cost ceteris paribus. In other words, mature MFIs are better to reach out to more clients for less money compared to younger MFIs, ceteris paribus. Yet, we found the impact on efficiency to be small (Standardized $\hat{\beta}$ = -0,080). MFIs lending methodology does not have a significant effect on cost per client, in contrast to the large significant effect we found in the other two regression models. Furthermore we find lending methodology significant in WLS, transformed and robustness checks where solidarity groups are most efficient. It is important to notice that individual lending increases the cost per client but reduces the OEP and OEA ratio. It is more expensive to service a larger loan than a small one. In other words, individual lenders are more expensive in absolute terms than group lenders. Yet, it is relatively more efficient for an MFI to focus on individual lending since it builds up a smaller client portfolio that tends to borrow larger amounts. We did not find any evidence of effect on the efficiency regarding MFIs area of intervention in the primary model, but urban turned out significant in WLS and transformed indicating that urban is less efficient than urban and rural. Complementary results are found in OEP ratio model. We also found that cost per employer, loan outstanding average and credit officer ratio has a strong significant effect on the cost per credit client. These three variables, together with credit officer productivity are significant and highly influence on all of the efficiency measurements. Loan outstanding average turned out to be the most influent efficiency driver on all efficiency measurements. It is important to notice that increased loan outstanding average increases the cost per client but reduces the OEP and OEA ratio. This can be explained by larger loan outstanding average achieving scale benefits, thereby reducing operating OEP and OEA. But at the same time it is a little more expensive to service a large loan than a small loan. In other words, increasing loan outstanding average reduces costs relatively, but not in absolute terms. Unlike the other two models, we did not find size significant in the CC model. Our findings imply that even though some MFIs have considerable amount of assets, they do not necessarily have a large client base. Moreover they are not able to exploit economies of scale in order to decrease cost per borrower and increase outreach. EECA region and Latin America has significantly lower cost per client compared to Africa. We found no significant differences between the MENA region, Asia and Africa.

5.4 Additional analyses and robustness checks

This section consists of regression results from additional analyses and robustness check. To adjust for violated assumptions we performed weighted least squared regressions and transformed model regressions. We also run regressions, leaving out the variables not significant in the initial model, and regressions with data from year -1. We have assumed that all dummy variables from year -1 are equal to the dummy variables in year 0. Our regression models in the previous section are referred to as initial OLS models

Models with only significant variables from the initial regression models included

Comparing the results in table 5-15 with the initial models we can see that most of the significant variables are more or less unaffected when leaving out variables that are not significant. The adjusted R^2 are identical to the initial OLS OEP ratio model and actually increasing compared to the initial OLS CC model, indicating that non-significant variables only added noise to the models. The initial OLS OEA ratio model has an adjusted R^2 of 0,5 compared to 0,413 in the model in table XX, which indicates that some explanatory information are left out of the model. Market competition is no longer significant in the new model, and since market competition is only significant at a ten percent level in the initial model, we should be careful two draw strong-held conclusions about market competitions effect on the efficiency. The new model confirms that EECA region and Latin America are more efficient then Africa, but not as much as the initial model indicated.

Table 5-15: Only significant variables from the initial regression models are included

Variables	$\hat{\beta}$ **OEP ratio model**	$\hat{\beta}$ **OEA ratio model**	$\hat{\beta}$ **CC model**
(Constant)	0,87871**	0,51600**	166,520**
COProd	-0,00033**	-0,00016**	-0,160**
CE	0,00001**	0,00001**	0,008**
LOA	-0,00009**	-0,00005**	0,070**
CO	-0,18606**	-0,14491**	-165,777**
VB	0,15593**	0,10737**	
SG	0,10579**	0,07610**	
Urban	0,03916**	0,02833**	
Size	-0,02742**	-0,01969**	
EECA	-0,09770**		-17,476**
LA	-0,05647**		-10,262*
MENA	-0,10895**		
Asia	-0,11371**		
MC	-0,00895		
Age			-1,255**
Dependent variable:	OEP ratio	OEA ratio	CC
R^2:	0,509	0,431	0,717
Adjusted R^2:	0,472	0,413	0,710
N:	249	248	247

**Significant at 5% level

* Significant at 10% level

Weighted least squared regression models

Our WLS regression results are presented in table 5-16. First of all, it is important to notice that the adjusted R^2 contains information about the dependent variables in the WLS models, not the initial models, and therefore can they not be compared. We are mainly interested in the significance level estimated by the WLS models. A large difference from the initial OLS model is that additional eight more variables have an effect on cost per client in the WLS model. We also found three more significant variables in the WLS OEP model and one more in the WLS OEA model. These findings should request to be careful about consequently reject that insignificant variables in the initial OLS model have an effect on the efficiency. Credit officer productivity, cost per employee, loan outstanding average and credit officer ratio are also significant in all of the WLS models. Market competition is not significant in the WLS regressions, which fortifies our earlier remarks about the market competition. Our WLS regression brings forth some interesting findings about the significant effect of offering pure financial services or not. It claims that specialized MFIs are less efficient then other MFIs, ceteris paribus. This goes against what has been found by Lensink and Mersland (2009c), and in our initial models. The age variable is significant in the WLS OEP model, but not in the OLS OEP model. The urban variable is significant in the WLS CC model, but not in the other two WLS models. This is complete opposite of what was found in the initial OLS models. The performance pay variable was the least significant variable in the OLS models, but it is significant in the WLS CC model. All region variables are now significant for the WLS CC model.

Table 5-16: Regression results of the Weighted Least Squared models

Variables	$\hat{\beta}$ **WLS OEP model**	$\hat{\beta}$ **WLS OEA model**	$\hat{\beta}$ **WLS CC model**
WLS factor	0,48240**	0,64997**	163,406**
WLS COProd	-0,00021**	-0,00015**	-0,150**
WLS MC	-0,00382	-0,00296	-1,770
WLS PureFS	0,04096**	0,02806**	11,290*
WLS Age	-0,00231**	-0,0094	-0,920**
WLS VB	0,16519**	0,11438**	-7,923
WLS SG	0,09978**	0,06897**	-12,197*
WLS Urban	0,02627*	0,01127	16,665**

WLS Rural	0,01150	-0,01496	-6,347
WLS CE	0,00001**	0,00001**	0,004**
WLS LOA	-0,00005**	-0,00005**	0,074**
WLS CO	-0,15119**	-0,06606*	-114,112**
WLS PerP	-0,00783	0,00635	-13,776**
WLS Size	-0,01457**	-0,02829*	-2,130
WLS MENA	-0,15307**	-0,01026	-42,907**
WLS EECA	-0,19795**	-0,00296	-66,670**
WLS LA	-0,13392**	0,00605	-42,094**
WLS Asia	-0,16074**	-0,01401	-46,647**
Dependent variable:	WLS OEP	WLS OEA	WLS CC
R^2:	0,891	0,910	0,982
Adjusted R^2:	0,882	0,902	0,981
N:	249	248	247

**Significant at 5% level

* Significant at 10% level

Transformed regression models

Our transformed regression models are presented in table 5-17. We did not find much deviation in the results comparing the transformed OEP and OEA model with the initial OLS OEP and OEA model, only that market competition is not significant in the transformed OEP model, and pure financial service and Asia are significant in the transformed OEA model. Some more deviation from the initial OLS model was found in the transformed CC model; pure financial service, loan methodology and area of intervention are significant, and age is no longer significant. We also found some change in regional significance; EECA region and Latin America are not significantly more efficient then Africa, but Asia is.

Table 5-17: Regression results of the transformed models

Variables	$\hat{\beta}$ OEP^{0,2} **model**	$\hat{\beta}$ OEA^{0,2} **model**	$\hat{\beta}$ $CC^{0,2}$ **model**
(Constant)	1,07973**	0,98111*	2,85398**
COProd	-0,00020**	-0,00015**	-0,00086**
MC	-0,00300	-0,00013	0,00543
PureFS	0,01771	0,02550**	0,11033**
Age	-0,00084	-0,00035	-0,00198
VB	0,07762**	0,08170**	-0,02263
SG	0,04915**	0,04839**	-0,07229**

Urban	0,01815*	0,01999**	0,06697**
Rural	0,00183	0,00879	0,00248
CE	0,00001**	0,00001**	0,00004**
LOA	-0,00006**	-0,00005**	0,00016**
CO	-0,11012**	-0,08175**	0,95610**
PerP	-0,00416	0,00206	-0,00946
Size	-0,01389**	-0,01708**	-0,00941
MENA	-0,04551*	-0,02100	-0,02937
EECA	-0,05004**	-0,00615	0,00250
LA	-0,02390*	-0,00163	0,00868
Asia	-0,07072**	-0,02876*	-0,20758**
Dependent variable:	OEP_0.2	OEA_0.2	CC_0.2
R^2:	0,572	0,571	0,818
Adjusted R^2:	0,540	0,539	0,805
N:	249	248	247
**Significant at 5% level			
*Significant 10% level			

Robust OLS regression models with data from year -1

Robust OLS regression models with data from year -1 can be seen in table 5-18. Starting with the robust OEP model, we found that the age variable is significant in the OEP ratio model, which supports the findings in the WLS OEP model. Yet, we did not find age significant in the initial OLS model. The urban and cost per employ variable and the three regions MENA, EECA and LA are not significant in the robust OEP ratio model, despite significance in all of the other four OEP ratio models. Moving to the robust OEA ratio model we found that the pure financial variable is significant at a ten percent level, which support the findings in the transformed OEA ratio and WLS OEA ratio model. We did not find urban to be significant, similar to the findings in the WLS OEA ratio model. The robust OEA ratio model is the only model where credit officer ratio is not significant. Asia is a significant region in the robust OEA ratio model. Finally, the robust CC model found market competition to be significant at a ten percent level, and solidarity group lending significant at a five percent level. On the other hand we did not find the age and the cost per employee variable significant.

Table 5-18: Regression results from OLS models with data from year -1

	$\hat{\beta}$ **OEP ratio model**	$\hat{\beta}$ **OEA ratio model**	$\hat{\beta}$ **CC model**

(Constant)	0,90272**	0,51284**	254,266**
COProd	-0,00022**	-0,00012**	-0,099**
MC	-0,00646	0,00142	-8,902*
PureFS	0,03627	0,03384*	21,255
Age	-0,00412**	-0,00116	-1,599
VB	0,22989**	0,13046**	30,370
SG	0,20118**	0,08839**	-50,514**
Urban	0,01717	0,01043	4,750
Rural	0,02168	0,00387	-26,111
CE	0,00001	0,00001**	0,002
LOA	-0,00005**	-0,00005**	0,113**
CO	-0,22205**	-0,05297	-143,407**
PerP	-0,03432**	-0,02075	-8,256
Size	0,04132	-0,00234**	17,115
MENA	-0,04840	-0,00587	-13,415
EECA	0,00110	-0,00151	37,072
LA	0,01295	-0,00324	20,425
Asia	-0,15899**	-0,08971**	-43,565
Dependent variable:	OEP ratio	OEA ratio	CC
R^2:	0,350	0,412	0,424
Adjusted R^2:	0,306	0,372	0,386
N:	271	271	271

**significant at 5% level
*significant at 10% level

Summary of additional analyses and robustness check

Our additional analyses and robustness checks reveals some deviation from the initial models. However, we believe that the deviations put more doubt on the rejections of variables rather then they put doubt on the significance of variables. In other words, we should be careful about consequently refuse any effect because the variable is not significant in the initial OLS models. Moreover, the significant variables in the initial models are confirmed by the results in the additional models. One exception is the market competition variable that we do not believe is an adequate variable to measure the market competitions effect on MFIs efficiency. Pure financial services are not significant in any of the initial OLS models, but it is significant in one or more of the additional OEP ratio, OEA ratio and CC models. We also found evidence in the additional analyses that urban area of intervention is less efficient then urban and rural area of intervention.

5.5 Summary of the models

Dependent variables	Models	COProd	MC	PureFS	Age	VB	SG	Urban	Rural	CE	LOA	CO	PerP	Size	MENA	EECA	LA	Asia
	Hypotheses	-	+ or -	-	-	+and-*	+and-*	-	+	+	-and+*	-	-	-				
OEP ratio model	OLS model	-	-			+	+	+		+	-	-		-	-	-	-	-
	OLS significant model	-				+	+	+		+	-	-		-	-	-	-	-
	WLS model	-		+	-	+	+	+		+	-	-		-	-	-	-	-
	Transformed model	-				+	+	+		+	-	-		-	-	-	-	-
	Year -1 robust model	-			-	+	+				-	-		-				-
OEA ratio model	OLS model	-				+	+	+		+	-	-		-				
	OLS significant model	-				+	+	+		+	-	-		-				
	WLS model	-		+		+	+			+	-	-		-				
	Transformed model	-		+		+	+	+		+	-	-		-				
	Year -1 robust model	-		+		+	+			+	-			-				-
CC model	OLS model	-			-					+	+	-				-	-	
	OLS significant model	-			-					+	+	-				-	-	
	WLS model	-		+	-		-	+		+	+	-	-		-	-	-	-
	Transformed model	-		+			-	+		+	+	-						-
	Year -1 robust model	-	-				-				+	-						

+ if the independent variable increases (decreases) then the dependent variables increases (decreases).

- if the independent variable decreases (increases) then the dependent variable increases (decreases).

Lower dependent variables indicate higher efficiency.

* The direction depends the dependent variable.

Table 5-19: Summary of models

6. CONCLUSIONS, IMPLICATIONS AND NEED FOR NEW RESEARCH EFFORTS

This study identified efficiency drivers and determined their effect on the overall cost efficiency of MFIs. The results presented from this study support some earlier findings and provide some new ones. 15 of 17 variables had a significant effect on one or more of the cost efficiency measurements and 8 of the 11 hypothesis in this study were supported by the results.

According to the findings we found that credit officer productivity, cost per employee, loan outstanding average and credit officer ratio were significant for all measurements. This is consistent with previous studies by Luzzi and Weber(2006), Baumann (2004), Gonzales(2007), Hermes et.al (2008) and others. Our findings suggest that MFIs should increase the number credit clients per credit officers and increase the number of credit officers relative to management staff in order to increase the overall cost efficiency. Our findings also suggest that more cost-effective operations can be obtained with less expensive employees. More important we find that higher average loan amount have a large impact on the overall cost efficiency of MFIs. Considering outreach and mission drift, we can conclude that it is crucial for the MFIs to focus on cost minimizing in order to avoid mission drift. This confirms what is found in Mersland and Strøm (2008a) and (Freixas & Rochet, 2008). The findings also indicate that MFIs providing non-financial services are more efficient then MFIs who only provides financial services. This is inconsistent with our hypothesis and the findings in Lensik and Mersland (2009c). We also found that MFIs operating in both rural and urban markets are more efficient then MFIs operating in urban markets, which are inconsistent with our hypothesis and the findings in Luzzi and Weber (2006). It is reason to believe that higher input prices in urban areas, especially on labor influence more on the cost-efficiency then lower technology and population density in rural areas. We did not find that performance pay has an effect on the cost-efficiency of MFIs. This finding suggests that MFIs incentive schemes are designed to stimulate other areas like better repayment rates or growth instead of cost-efficient operations. Considering the challenges related to efficiency in MFIs we question whether this is a wise design of staff incentives and recommend further research on these issues.

We demonstrated earlier in the introduction, building upon Hulme and Mosley (1996a, p. 19), that the loan rate is much affected by the MFIs administrative cost. Moreover, Gonzalez (Gonzalez, 2007) reports that operational costs represented about 2/3 of charges to borrowers, making them the largest component of the interest rates. In order to reduce the cost of credit for poor and low income people MFIs have to focus on more cost-efficient operations. We advertise for more research on cost-efficiency of MFIs, hence large improvements can be made and studies on this ground are rather limited.

The findings are based on data collected from 377 MFIs in 74 countries. The dataset contains only data from MFIs that voluntarily have agreed to open their accounts for scrutiny and rating, and accepted that the reports become public available. Therefore it is important to be aware of possible differences between the rated and the non rated MFIs. There is also reason to believe that accounting principles could be different from country to country and socio economic factor may influence the consistency of the data. Concerning the market competition our findings indicates that the variable applied is not adequate to measurer the effect of market competition, and we suggest that adjustments should be made to the variable to better measure the effect of market competition.

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