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Department of Banking and Finance
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How does social performance affect financial performance in microfinance?

Master Thesis in Banking and Finance

Sergey Keller

Full Text Version

CSP Thesis Series no. 24 (2019)

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Executive Summary

This thesis examines the relationship between social performance (SP) and financial performance (FP) of microfinance institutions (MFIs). Despite a large body of literature using standard SP measures (i.e. average loan size and percentage of female borrowers), as well as some studies using alternative SP metrics, academics have not yet reached an unambiguous opinion about the general effect of SP on FP.

Thus, the objective of this study is to conduct an in-depth analysis on the topic in two steps. Firstly, it performs empirical analysis using standard indicators of SP and compares the results to previous literature. Secondly, it constructs and adds various alternative SP metrics to the standard measures of SP and compares the results of new models to the standard ones. This paper critically reflects on the additional value of expanding the standard models with alternative SP variables.

The data used in this thesis are provided by UZH DBF's Center for Sustainable Finance and Private Wealth. The dataset contains panel data which is defined as observations of various MFIs at several points in time. The full dataset includes 16'918 year-MFI observations from 1995 to 2014. This dataset represents the aggregation of "diamond" and "legal" history datasets with other purchased datasets. The original datasets were obtained from Microfinance Information eXchange database (MIX). Furthermore, this thesis constructs additional SP metrics from the original MIX data and expands the dataset. The dataset is analysed through fixed effects generalized least squares (FEGLS) method.

The empirical results of the thesis confirm the previous findings on interaction between standard indicators of SP and FP. The findings show that smaller loans and higher percentage of female borrowers have neutral effect on profitability measured by return on assets (ROA). Both smaller loans and higher percentage of female borrowers decrease efficiency measured by operating expenses (OPEXP) divided by average gross loan portfolio (GLP). Lastly, both smaller loans and higher percentage of women borrowers increase productivity measured by clients per staff member.

The addition of alternative metrics of SP indicates that better SP has a slightly positive impact on profitability. Both higher percentage of retained borrowers and lower staff turnover ratio have a positive effect on ROA. Greater offices network coverage seems to decrease profitability.

The models with alternative SP measures further suggest that higher outreach has a neutral impact on efficiency. A larger number of rural borrowers and higher percentage of retained borrowers seem to increase efficiency. Greater offices network coverage, presence of saving products, and larger number of new borrowers have a negative impact on efficiency.

Lastly, the empirical results of models with added alternative SP metrics reveal that better SP increases productivity. Higher percentage of retained borrowers, larger number of new borrowers, and lower staff turnover ratio have a positive impact on profitability. Meanwhile, greater offices network coverage decreases productivity.

All models with alternative proxies for SP demonstrate higher explanatory power measured by R-squared compared to the model with only standard proxies.

This thesis contributes to the existing literature by providing additional empirical evidence on the topic and developing proxies for more SP dimensions recently designed by practitioners. It is worth emphasizing that outreach metrics are the tools that help to answer the ultimate question: Do MFIs give poor populations an opportunity become self-sufficient? This question cannot be answered with the existing data on microfinance. Thus, a possible policy implication would be to incentivize various organizations that develop social metrics and platforms that collect microfinance data to closely work with academia. This is the only way to ensure collection of data that can be practical for future research.

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List of Abbreviations

ALB	Average Loan Balance
CERISE	Comité d'Échange, de Réflexion et d'Information sur les Systèmes d'Epargne-crédit
FD	First Differencing
FE	Fixed Effects
FEGLS	Fixed Effects Generalized Least Squares
FEMALE	Percentage of Female Borrowers
FP	Financial Performance
GLP	Gross Loan Portfolio
GNI	Gross National Income
MFI	Microfinance Institution
MIX	Microfinance Information eXchange
MNO	Mobile Network Operator
NBFI	Nonbank Financial Institution
NGO	Non-Governmental Organization
OLS	Ordinary Least Squares
OPEXP	Operating Expenses
OSS	Operational Self-Sufficiency
POLS	Pooled Ordinary Least Squares
RE	Random Effects
ROA	Return on Assets
SP	Social Performance
SPI	Social Performance Indicator
SPTF	Social Performance Task Force
SR	Social Responsibility
UEM	Unobserved Effects Model

1 Introduction

The microfinance industry includes all financial services specifically designed for poor populations. The main goal of this industry is to help impoverished people to become self-sufficient. Although this industry has emerged only four decades ago, it has already gone through a tremendous transformation from inefficient subsidized rural credit programs of the past to resourceful financial service providers of the present. However, many financially sustainable microfinance providers struggle to fulfil the mission of microfinance. On the other hand, many microfinance providers that serve many poor people are not profitable. Thus, the question arises of whether or not SP and financial sustainability are compatible.

The existing research on the topic indicates mixed results. Most of the studies that use only two, albeit paramount, standard proxies for outreach (i.e. average loan size and percentage of women borrowers) conclude that the relationship between SP and FP is ambiguous. Other academics that have recently developed more detailed and practice oriented alternative metrics of SP dimensions indicate that SP and FP may be compatible. However, the results are influenced by the choice of data sample.

The objective of this study is twofold. First, it analyses the influence of standard proxies for SP on key FP indicators and compares the results with previous literature. Second, it develops measures for various SP dimensions taken from previous studies and adds them to the standard proxies for SP. Thus, the thesis critically reflects on the additional value of expanding the standard models with alternative SP variables.

The data used in this thesis are provided by UZH DBF's Center for Sustainable Finance and Private Wealth. The dataset contains panel data which is defined as observations of various MFIs at several points in time. The full dataset includes 16'918 year-MFI observations from 1995 to 2014. This dataset represents the aggregation of "diamond" and "legal" history datasets with other purchased datasets. The original datasets were obtained from MIX. Furthermore, this thesis constructs additional SP metrics from the original MIX data and expands the dataset. The dataset is analysed through FEGLS method.

The empirical results of the thesis confirm the previous findings on interaction between standard indicators of SP and FP. The findings show that smaller loans and higher percentage of female borrowers have neutral effect on profitability measured by ROA. Both smaller loans and higher percentage of female borrowers decrease efficiency measured by OPEXP divided by average GLP. Lastly, both smaller loans and higher percentage of women borrowers increase productivity measured by clients per staff member.

The addition of alternative metrics of SP indicates that better SP has a slightly positive impact on profitability. Both higher percentage of retained borrowers and lower staff turnover ratio have a positive effect on ROA. Greater offices network coverage seems to decrease profitability.

The models with alternative SP measures further suggest that higher outreach has a neutral impact on efficiency. A larger number of rural borrowers and higher percentage of retained borrowers seem to increase efficiency. Greater offices network coverage, presence of saving products, and larger number of new borrowers have a negative impact on efficiency.

Lastly, the empirical results of models with added alternative SP metrics reveal that better SP increases productivity. Higher percentage of retained borrowers, larger number of new borrowers, and lower staff turnover ratio have a positive impact on profitability. Meanwhile, greater offices network coverage decreases productivity.

All models with alternative proxies for SP demonstrate higher explanatory power measured by R-squared compared to the model with only standard proxies.

This thesis contributes to the existing literature by providing additional empirical evidence on the topic and developing proxies for more SP dimensions recently designed by practitioners. It is worth emphasizing that outreach metrics are the tools that help to answer the ultimate question: Do MFIs give poor populations an opportunity become self-sufficient? This question cannot be answered with the existing data on microfinance. Thus, a possible policy implication would be to incentivize various organizations that develop social metrics and platforms that collect microfinance data to closely work with academia. This is the only way to ensure collection of data that can be practical for future research.

The remainder of this thesis is organized as follows. Section 2 presents a concise development of microfinance and gives a brief overview of the industry today. Section 3 analyses previous literature. Section 4 states objective and describes data sample, research method, variables, and hypotheses. Section 5 illustrates the results of empirical analysis. Section 6 concludes and gives an outlook for future research.

2 Evolution of Microfinance

This chapter defines the term microfinance and gives a brief introduction to the history and development of microfinance industry. First, the definition and main purpose of microfinance are given. Next, the emergence and evolution of microfinance are analysed. Finally, current state of industry and summary conclude this chapter.

2.1 Definition of Microfinance

The term microfinance includes all financial services specially designed for low-income groups. The core component of microfinance is microcredit which is defined as provision of small loans to poor people (Grameen Bank (2018, 24 March 2019)).

According to CGAP (2006a, 24 March 2019), microfinance clients use access to financial services for three main reasons. First, microfinance allows low-income groups to handle life-cycle events. Such events are defined as occasions that happen only once in a lifetime like birth, marriage, death or reoccurring incidents like holidays, educational expenses, crops purchase that are typical for most households. Second, microfinance can significantly increase resistance of many poor people to emergencies such as personal crises. These crises include loss of employment, sickness, theft, and many others. Third, microfinance helps poor people to seize opportunities and invest in activities and assets. One of the several types of opportunities is business investment. Furthermore, low-income households use loans to improve their living conditions and may invest in costly items such as repair of house or additional home appliances.

2.2 Subsidized Rural Credit Programs in 1960s and 1970s

The idea of subsidized rural credit is derived from the supply-leading finance theory emerged in the 1940s and 1950s. This theory is focused on provision of loans before demand for credit appears. The emergence of this theory is shaped by the prevailing ideas after independence of many today's developing countries. These countries believed that rural areas were the main driver of economic growth and national development. However, most farmers had insufficient capital and savings capacity to be able to expand their businesses without additional financing. Moreover, many economists of that time claimed that the rural businesses could not pay commercial interest rates (Robinson (2001)).

Consequently, many governments and donors around the globe started large-scale subsidized credit programs in the late 1960s and 1970s. The rationale behind the most programs at that time was straightforward: subsidized credit can help large number of farmers to start or expand their businesses and therefore increase their income. Unfortunately, most of the credit programs failed to reach their goals and caused a lot of criticism from academics and public (Robinson (2001)).

2.3 Emergence of Microfinance in 1980s

Microfinance can be traced back to the invention of group lending model in 1976. The group lending is a revolutionary financial innovation that helped to overcome most of the problems which plagued the subsidized credit programs. Furthermore, the group lending also helped to mitigate agency problems such as moral hazard and adverse selection (Sengupta and Aubuchon (2008)).

The early success of the group lending model led to foundation of Grameen Bank in 1983 following a proclamation of the Bangladeshi president. Grameen means "of the village" and it emphasizes the fact that cooperation of villagers is required for smooth operation of a bank (Sengupta and Aubuchon (2008)).

2.4 The Current State of Microfinance

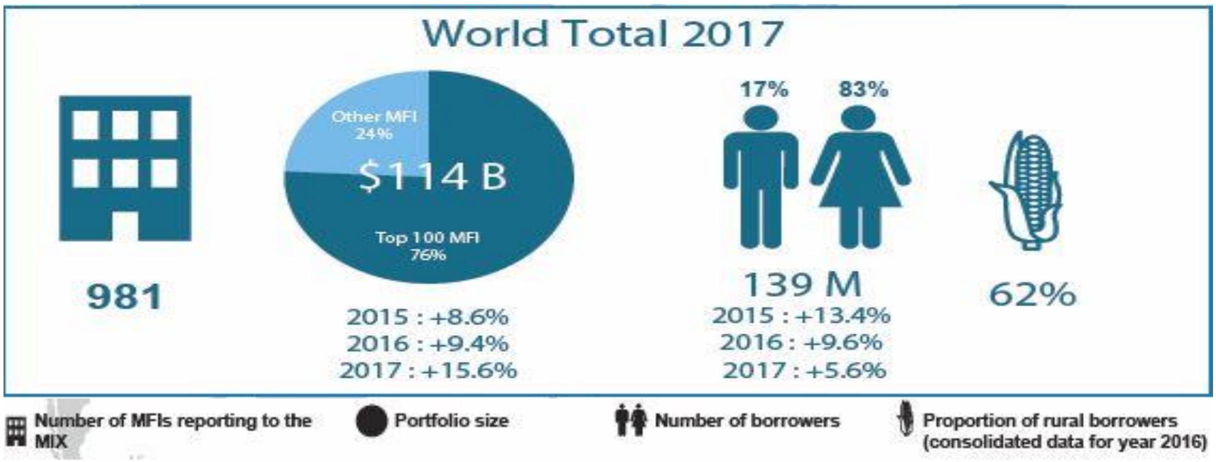
The term microfinance was recently replaced with digital financial inclusion which means digital access to formal financial services for excluded and underserved populations (CGAP (2014, 24 March 2019)). The main reason of this development was the fact that microcredit did not manage to achieve its intended goal of reaching large scale due to large transaction costs of microcredit products (Francis, Blumenstock, and Robinson (2017)).

Current providers of financial services can be categorized into four classes by contractual relationship with a customer: a universal bank which offers a basic account for transactional services and value storage which can be accessed through a mobile device or a bank card, a niche bank which offers the same account, a mobile network operator (MNO) which issues e-money, and a nonbank and non-MNO entity which issues e-money. All operational setups require three elements: a digital platform, a distribution network, and an access device. The digital platform is an essential part of a digital financial inclusion model because it facilitates execution of transactions and stores transaction data as well as electronic value of client's funds. Distribution network is a bridge between the digital platform and users. It helps customers to convert physical money into electronically stored value and transmits and receives the transaction details. The last part of the digital ecosystem is the digital device or a tool that can enable connection to the digital device. The digital device such as a mobile phone is used to connect to the digital platform and use financial services or access electronic funds (CGAP (2014, 24 March 2019)).

Although digital financial services provide a lot of benefits for clients, the potential setbacks must be considered as well. First, electronic storage and management of data as well as custody of funds is normally performed by one bank and nonbank entity. Thus, real-time accuracy and reconcilability of data between the bank and its MNO might be a problem. Additionally, some holders of funds do not participate in deposit insurance system and thus put their customers at risk. Second, quality and usability of digital services might be affected by disruption of service or loss of data and privacy or security breaches. Third, use of third-party digital service providers results in new operational, financial crime and consumer protection risks (CGAP (2014, 24 March 2019)). Consequently, banks must train and supervise their agents to ensure high quality of financial services and safeguard their customers from new digital hazards.

Despite tremendous growth of the digital financial providers for the poor, conventional MFIs remain the main driver of financial inclusion. At the end of 2017, there were 981 MFIs reporting to MIX which served approximately 139 million microfinance clients around the world. The total estimated loan portfolio was around 114 billion dollars with the top 100 largest institutions, ranked by loan portfolio, serving 76% of both borrowers and loan portfolio. The women accounted for 83% of all microfinance customers what emphasizes the historical focus of MFIs on serving primarily female clients. The rural borrowers represent 62% of the clients served by MFIs at the end of 2016 (Convergences (2018, 24 March 2019)). Figure 1 demonstrates the key figures of financial inclusion in 2017.

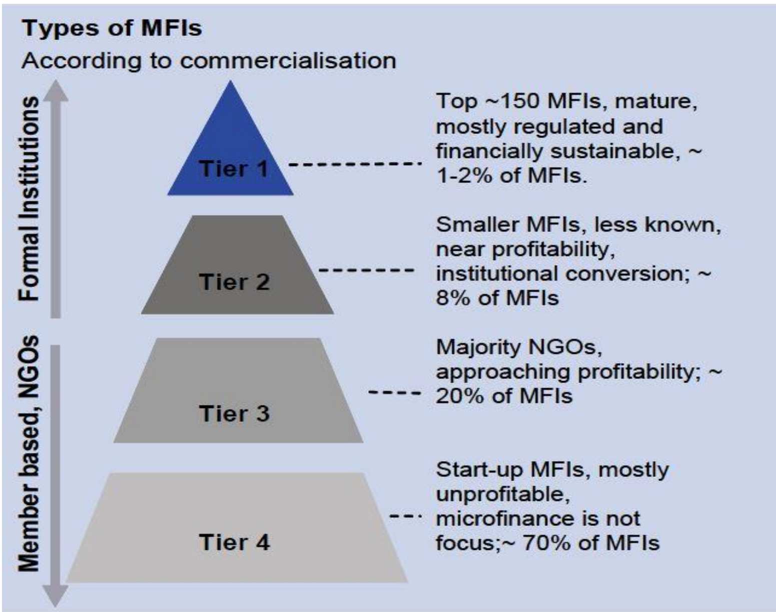
Figure 1: Key Figures of Financial Inclusion in 2017



Source: Convergences (2018)

Deutsche Bank Research (2008, 24 March 2019) estimated that there are over 10’000 MFIs operating all over the world. They are presented in various organizational forms such as non-governmental organizations (NGOs), private and commercial banks, credit unions, and different combinations of these forms. The entire universe of MFIs can be divided into four major tiers. The first tier includes mostly regulated and financially sustainable MFIs that are run by an experienced management team. This group is represented by approximately 150 MFIs or around 2% of all existing MFIs. The second tier comprises successful but smaller MFIs that have already achieved or approaching profitability. They are often NGOs in the process of transformation into regulated MFIs. Such institutions account for 8% of all MFIs. The third tier mainly consists of NGOs which are approaching profitability but have insufficient capital, weak management information systems, or other problems. They make up 20% of total number of MFIs. The last tier is composed of unprofitable MFIs which are usually start-ups or organizations which do not primarily focus on microfinance. These institutions amount to 70% of all MFIs. Figure 2 illustrates the classification of MFIs.

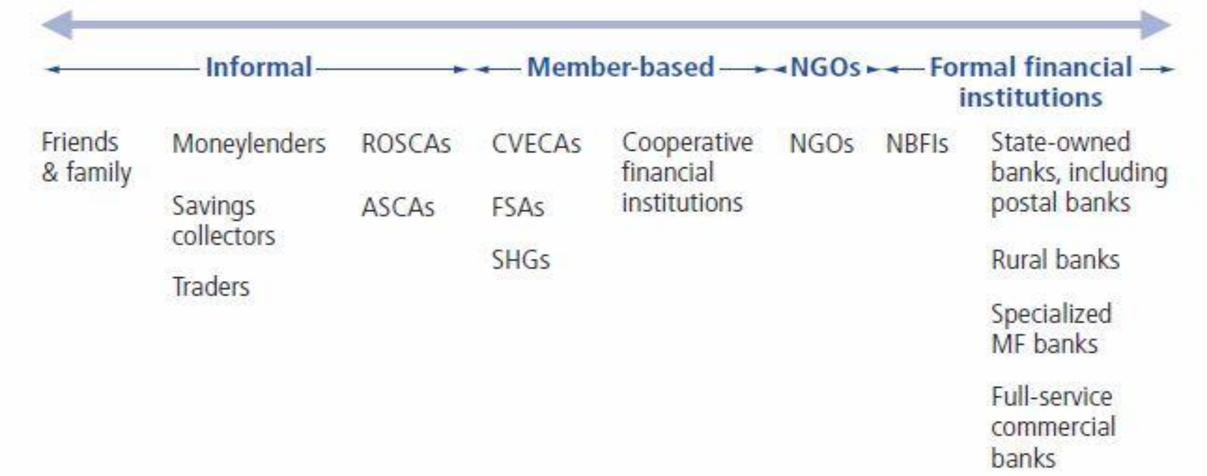
Figure 2: Classification of MFIs



Source: Deutsche Bank Research (2008)

The conventional microfinance providers can be also classified on a range from informal to formal by organizational structure. The most informal suppliers of financial services have very simple or non-existing organizational structure and they are never regulated. Typical examples of such suppliers are friends and family, moneylenders, and rotating savings and credit associations. The member-based organisations such as credit unions and cooperatives represent more formal microfinance providers. They are financed by members' funds that usually come from savings. NGOs tend to be informal organisations in their start-up phase and shift to more formal organisational structure as they grow large and often transform into licensed financial intermediaries. They are usually financed by donors or subsidies and switch to commercial sources of funding after becoming financially sustainable. The most formal institutions are nonbank financial institutions (NBFIs) and various types of banks (CGAP (2006a, 24 March 2019)). Figure 3 demonstrates the spectrum of financial service providers.

Figure 3: Spectrum of Financial Service Providers



Note: ROSCAs = rotating savings and credit associations; ASCAs = accumulating savings and credit associations; CVECAs = Caisses Villageoises d'Épargne et de Crédit Autogérées; FSAs = financial service associations; SHGs = self-help groups; NGOs = nongovernmental organizations; NBFI = nonbank financial institution.

Source: CGAP (2006a)

2.5 Summary of Evolution of Microfinance

The microfinance industry as we know it today has emerged only four decades ago. Nevertheless, it has undergone a tremendous transformation from the inefficient and wasteful subsidized rural credit programs of the past to the well organized and resourceful financial service providers of the present. Despite an enormous progress made in theory of microfinance, practice did not follow the lead. Most of the microfinance providers did not manage to achieve large scale or financial sustainability and thus still rely on subsidies and donors' funds. Consequently, the conventional microfinance products are being replaced by the innovative digital financial services. Although the new approaches of delivering financial services to the excluded populations are gaining popularity, it remains to be seen whether they will become an industry standard in the future.

3 Literature Review

This section analyses previous research on the topic of the thesis. First, the academic papers that use standard measures are described. Second, alternative literature on the topic is examined.

3.1 Standard Measures

Most of the existing academic papers that investigate the relationship between SP and FP of MFIs are using two variables to measure SP. The first standard measure of SP is an average loan balance (ALB). It is the most common indicator of MFI outreach to the poor among microfinance investors and donors (Mersland and Strøm (2010)). The economists believe that low values of ALB indicate higher outreach to poor populations and thus better SP. The second standard indicator of SP is a percentage of female borrowers (FEMALE). Since one of the goals of microfinance is to focus on the female clients due to various social and financial reasons, this measure is included in many studies with higher values indicating better SP. The research papers described below are using ALB and FEMALE to investigate how they affect FP of MFIs. These papers were picked because they summarize the common view of academia on the research is this field.

One of the papers written by Meyer (2019) examines the relationship between social outreach and financial return of MFIs. The author argues that previous research on the topic demonstrates inconsistent results. Some researchers claim that MFIs focused on SP have better FP. However, most studies fail to find any relationship between SP and FP of MFIs. Thus, the main goal of this paper is to quantify how standard SP measures affect FP of MFIs.

This study uses the data file which includes 1’805 observations over the period 2004 – 2013 obtained from MIX. Only the MFIs with five diamonds rating are included into an empirical analysis. This approach may cause a self-selection bias in the data sample which is not addressed later in the study. The author uses a random effects (RE) model, a fixed effects (FE) model, and a Hausmann-Taylor model to analyse the data. The robustness check is performed through a FE regression with dummy variables. The two measures of SP are ALB divided by average gross national income (GNI) and FEMALE. The FP is measured by nominal and real portfolio yield, OPEXP divided by average total assets, ROA, return on equity, operational self-sufficiency (OSS), and profit margin. Furthermore, several MFI-specific control variables (e.g. age, legal status, etc.) are included into the empirical analysis. The results of this research indicate that MFIs impose higher interest rates on female borrowers and clients with smaller loans. However, the OPEXP also increase along with the interest rates. Thus, the researcher finds a neutral effect on return measures, since they are influenced by both the costs and the yield. Additionally, the author tests the empirical results based on institutional types and geographies of MFIs and finds that the results hold. Nevertheless, the writer emphasizes that future research must focus on specific markets and take size of institutions into account.

Quayes (2015) studies whether there is a possible trade-off between financial sustainability and outreach. The researcher analyses previous literature on the topic and finds that some studies show a clear evidence of trade-off due to decreased efficiency caused by deeper outreach. However, other papers claim that deeper outreach leads to increased efficiency and thus reject any trade-off between outreach and financial sustainability. Thus, the objective of this study is to investigate the influence of depth of outreach on FP of MFIs.

The data are collected from MIX. The main selection criteria for the data sample used in an empirical analysis are the presence of four consecutive years of observations and the rating equal to at least three diamonds. The final data sample is an unbalanced panel with 764 MFIs over the period 2003 – 2006. However, only 247 MFIs provided complete information for all four years. The author uses a two-stage least squares regression for each year of observations in the empirical analysis. The independent variables are profit margin rate, ROA, and OSS. The explanatory variables are GLP, debt to equity ratio, total expense ratio, loan loss reserve ratio, and ALB divided by GNI. The ALB divided by GNI is an instrumented variable with cost per borrower used as an instrument. The chosen empirical method allows to get consistent estimates because the instrumental variable is correlated with ALB divided by GNI, but it is uncorrelated with an error term. The results of the study indicate that depth of outreach has a positive influence on FP. The results hold even when the regressions are estimated using FE, RE, and Hausman-Taylor methods for balanced and unbalanced panels. Furthermore, the robustness of the results is also confirmed by results from the regressions that include only four and five diamonds rating MFIs. However, the author does not discuss the self-selection bias driven by removal of MFIs with one and two diamonds rating. Thus, the results of the research might be biased.

D'espallier, Guerin, and Mersland (2013) investigate how focus on women affects overall FP of MFIs. The authors emphasize two main components of a profit function: repayment rates and operating costs. They claim that there are several reasons why a gender may influence repayments rates. First, the business activities conducted by women are more adaptable to the regular repayments typical for most microloans (Johnson (2004)). Second, some studies have found that women are more risk-averse than men and thus they do not take the loans which they cannot repay (Armendáriz and Morduch (2005) and Phillips and Bhatia-Panthaki (2007)). Third, women are more afraid of losing social capital and peer pressure, which are often used by MFIs in their lending methodologies. The researchers also explain why women may be associated with higher operating costs. First, female borrowers are more likely to request smaller loans which cause higher operating costs. Second, women exhibit lower literacy levels and therefore require more intense monitoring what results in higher staff and administrative costs. Third, a lot of female clients request tailor-made services that suit their needs, which are always very costly (Armendáriz and Labie (2011)). Thus, two empirical questions of this study are to define the characteristics of MFIs that target women and examine how does targeting female clients affect different performance drivers and overall FP.

The researchers use the data obtained from the rating assessment reports collected by rating agencies. The sample contains 398 MFIs from 73 countries worldwide. The ratings have up to ten years of data over the period of 2001 – 2010. The authors emphasize that their dataset does not contain a lot of small savings and credit cooperatives, but it is one of the most representative datasets available for the microfinance industry. Furthermore, the scientists claim that it avoids a large firm bias. The paper uses ordinary least squares (OLS) and logit methods to identify the characteristics associated with a focus on women. The influence of targeting women on FP is investigated through Hausmann-Taylor regressions. The dependent variables in the first regression are a percentage of women clients, a dummy if the MFI specifically targets female clients, and a dummy if the percentage of women is above average. The independent variables represent an international orientation, a lending method, ALB, and a legal status as well as some commonly used controls. The second regression uses a portfolio income, operational costs, funding costs and default costs as dependent variables. The independent variables are composed of different gender variables, and some controls are taken from previous literature. The results of the study indicate that MFIs with the focus on women exhibit higher international orientation, collective loan methods, lower ALB, and non-commercial legal status. Furthermore, lending to women is significantly related to lower default costs and higher operational expenses. The research shows that higher operational expenses associated with female borrowers are caused by nature of loans. The female borrowers often prefer the smaller loans which they receive through group lending methods what leads to increase in operational expenses. Lastly, the results show that MFIs targeting women are not able to convert better repayment rates into better FP measured by ROA. Thus, there is no significant relationship between the focus on female borrowers and FP of MFIs.

In conclusion, the previous research shows that the relationship between standard measures of SP and overall FP of MFIs is unclear. Some studies find positive link between the two, whereas other studies indicate a neutral relationship. Thus, the first step in my approach to tackle this issue would be to analyse the dataset which includes only standard measures of SP and compare my empirical findings to the previous literature.

3.2 Alternative Measures

Since the clear relationship between SP and FP of MFIs was not identified by using standard measures of SP, some academics constructed alternative measures of SP to solve this issue. The two papers described below represent the cornerstones of this thesis.

The paper by Gonzalez (2010) studies SP and FP of MFIs. The main objective of this paper is to discover and quantify both trade-offs and synergies between SP and FP goals of MFIs. The study uses the data of 208 MFIs in 2008 from MIX. The empirical analysis is performed through OLS. The dependent variables are productivity measured by borrowers per staff, portfolio quality measured by portfolio at risk over 30 days as well as write-off ratio, and efficiency measured by OPEXP divided by average GLP as well as cost per borrower as percentage of GNI per capita. The explanatory variables represent various social performance indicators (SPIs) developed by Social Performance Task Force (SPTF). The SPIs are constructed based on the answers to questions from the SPTF questionnaire. Most of the SPIs are either binary or categorical variables and thus their usability is limited. The first SPI used in this study is targeting of poor with three income levels: very poor, poor, and low-income. The rest of the independent variables are presence of non-financial services, training on SP, client retention, social responsibility (SR) to clients, and SR to staff. The author also uses some controls taken from previous literature. The empirical results with regards to productivity indicate that training on SP and higher client retention rates have a positive impact on productivity. Moreover, rural MFIs seem to be more productive than urban MFIs contrary to the common belief that operating in rural areas decreases productivity. The empirical results with regards to portfolio quality show that training of staff on SP improves portfolio quality. Lastly, the study confirms that targeting very poor or poor clients decreases efficiency. This outcome is based on the fact that poor borrowers request small loans which are associated with higher operating costs. The author emphasizes that the SPIs created by SPTF require further development because they do not allow to separate the individual effects of certain dimensions of SP. For example, training on SP cannot be separated from general training of MFIs and thus its individual effect cannot be quantified.

The study by Bédécarrats, Baur, and Lapenu (2012) conducts an empirical analysis of the relationship between SP and financial sustainability. The authors believe that ALB and number of female borrowers represent only one of many dimensions of SP. Thus, the researchers use SPI tool designed by Comité d'Échange, de Réflexion et d'Information sur les Systèmes d'Epargne-crédit (CERISE) in 2001. CERISE is a French non-profit organization that aims to measure and analyse SP to improve practices in microfinance sector (CERISE (2018, 7 December 2018)). The CERISE SPI tool is a questionnaire that analyses internal systems and organizational processes of MFIs to determine if they have the means to reach their social goals (CGAP (2007, 7 December 2018)). The questionnaire is divided into four dimensions as defined by SPTF with three criteria per dimension. The first dimension of the original SPI tool is called “Targeting and outreach”. The SP measures in this dimension assess the level of outreach to the poor and excluded populations. The first criterion of the first dimension is called “Geographic targeting”. This criterion defines whether MFIs operate in the remote areas which are close to the poor in terms of physical distance. The second criterion of the first dimension is called “Individual targeting”. This criterion defines if MFI caters to the particular groups of poor clients. The last criterion of the first dimension is called “Methodological targeting”. It analyses if the products and services offered by MFIs target poor or excluded customers. The second dimension of the original SPI tool is called “Adaption of services”. The SP measures in this dimension evaluate how well financial products provided by MFIs satisfy clients’ needs. The first criterion of the second dimension is called “Range of traditional services”. This criterion defines whether MFIs offer only lending or also any other types of financial services. The second criterion of the second dimension is called “Quality of services”. This criterion assesses the quality of financial services provided by MFIs. The third criterion of the second dimension is called “Innovative and non-financial services”. It reveals whether MFIs offer any unconventional and non-financial services. The third dimension of the original SPI tool is called “Benefits to clients”. The SP indicators in this dimension measure the economic and social benefits to clients created by financial services. The first criterion of the third dimension is called “Economic benefits to the clients”. This criterion evaluates whether financial services offered by MFIs improve socioeconomic status of their clients. The second criterion of the third dimension is called “Client Participation”. It reveals whether clients are involved in governance of MFIs. The last criterion of the third dimension is called “Client empowerment”. It assesses whether

MFIs contribute to empowerment and social capital building of their clients. The fourth dimension of the original SPI tool is called “Social responsibility”. The SP indicators in this dimension evaluate level of SR of MFIs towards their stakeholders. The first criterion of the fourth dimension is called “SR to employees”. This criterion investigates whether MFIs are socially responsible towards their employees. The second criterion of the fourth dimension is called “SR to clients”. It examines whether MFIs follow client protection principles. The third criterion of the fourth dimension is called “SR to the community and the environment”. It assesses whether MFIs contribute to improvement of local environment.

The data used for analysis were obtained from 344 SPI evaluations of 295 MFIs over the period of 2006 – 2011. The researchers use OLS to perform the empirical analysis. The dependent variables are productivity measured by the ratio of number of borrowers per staff member, portfolio quality measured by a sum of portfolio at risk at 30 days and write-off ratio, and efficiency measured by OPEXP. The explanatory variables are 12 criteria from CERISE SPI tool. The authors run regressions with all combinations of variables and use controls taken from previous literature. It is important to mention that the CERISE SPI tool indicators are only comparable among MFIs that belong to the same peer group. The results of the study show that productivity increases with geographic targeting and lower ALB, whereas a wider range of services has a negative impact on productivity. The portfolio quality seems to improve with a higher quality of services and a higher social responsibility to staff. Lastly, efficiency seems to decrease with a higher score for individual targeting, innovative and non-financial services, and social responsibility to clients. However, a wider range of products, a better quality of services, higher economic benefits to the clients, and a higher SR to community and environment have a positive impact on efficiency. The authors conclude that SP and FP are compatible. MFIs can achieve financial sustainability if they can find the right mix of SP practices. Thus, investments into social and responsible performance can help MFIs to fulfil double bottom line objective.

In conclusion, inclusion of the alternative SP variables into the analysis of the relationship between SP and FP of MFIs leads to belief that SP and FP are compatible. Therefore, the second step in this thesis would be to add various alternative SP indicators to the standard SP variables and compare the results to the standard models. Furthermore, the empirical analysis will also indicate whether more detailed SP metrics generate any additional value in terms of explanatory power.

4 Methodology

This chapter describes the objective of the thesis, the dataset used, the research method, and the variables used in empirical part of research. In the beginning, the objective is stated, and research design is explained. Later, the data source and dataset are described. Then, different research methods are analysed. Next, all variables used in the empirical section of this study are reported. And last, all hypotheses in the study are formulated.

4.1 Objective and Approach

The research aims to investigate how the main aspects of SP of MFIs affect their FP. The thesis uses a two-step approach to investigate this topic.

At first, it analyses a customized version of the global microfinance supply-side panel dataset, the MIX data, available at the DBF's Center for Sustainable Finance and Private Wealth. This dataset includes the FP indicators of MFIs as well as a detailed set of the SP indicators for a subset of the global dataset from 1995 to 2014. These data will be used to analyse the influence of standard SP measures on the key FP measures of MFIs. Consequently, thesis will critically compare its findings on the relationship between SP and FP with the previous studies in the literature.

Afterwards, the dataset is used to study the effect of alternative SP variables. The alternative SP indicators will be assigned to different dimensions following one of the methodological approaches and added to the standard SP measures. Thus, the thesis will critically reflect on the additional value of more detailed SP metrics and the potential explanatory power of adding such variables to the standard models used in the literature so far.

4.2 Data

The data used in this thesis are provided by UZH DBF's Center for Sustainable Finance and Private Wealth. The dataset contains the panel data which is defined as observations of various MFIs at several points in time. Moreover, it is an unbalanced panel meaning that MFIs are observed different number of times (Greene (2012)). The full dataset includes 16'918 year-MFI observations from 1995 to 2014. This dataset represents the aggregation of "diamond" and "legal" history datasets with other purchased datasets. The original datasets were obtained from MIX. Furthermore, this thesis constructs additional SP metrics from the original MIX data and expands the dataset.

MIX is a global platform that aggregates data on microfinance. Although the data are self-reported, they are considered to be of high quality because they are checked by in-house analysts after submission. Furthermore, all the data submitted to MIX are standardized to facilitate comparability (Ledgerwood (2013)).

Despite high quality and usability of MIX data, they may suffer from a self-selection bias due to an over-representation of the MFIs that are committed to financial sustainability and thus willing to comply with MIX's extensive reporting standards. Thus, there is a high chance that the MFIs reporting to MIX are the best-performers in the microfinance industry (Armendáriz and Labie (2011)). Fortunately, the self-selection bias is partly mitigated by the fact that the MIX database contains data on approximately 85% of microfinance clients (Ledgerwood (2013)). Nevertheless, the statistical inferences drawn from the MIX dataset cannot be valid for the entire microfinance universe.

The other problem in this dataset that may create issues for the research is overwriting of variables. When the researchers from University of Zurich were merging multiple datasets into one, they overwrote the misleading diamond rankings and legal status entries. Furthermore, the diamond ranking and legal status entries of some MFIs changed over the sample time range. The original values were overwritten with new ones for all years. Consequently, some descriptive statistics and results from the empirical models may not apply to the entire time range of the sample.

4.3 Research Method

The main motivation for using the panel data described in the previous chapter is to solve an omitted-variable problem. This problem arises when some independent variables, which influence dependent variable, are omitted from a regression. Thus, most models attribute the effect of missing variables on dependent variable to the estimated effects of explanatory variables in the model. This issue creates a bias in the estimation and leads to false inferences (Greene (2012)).

The unobserved effects model (UEM) is trying to solve the omitted-variable bias by introducing unobserved effects in panel data analysis. The unobserved effects are represented by the random variables which are drawn from a population along with the observed explained and explanatory variables. These effects can be interpreted as the features of MFI such as managerial quality or organisational structure that are given and remain persistent over time. It is worth writing down the general equation of UEM to better understand different components of the model:

$$y_{it} = x_{it}\beta + c_i + u_{it} \qquad t = 1,2,\dots,T \tag{1}$$

The unobserved effect c_i is also called an individual effect because it is assumed to be unique for each MFI in a dataset. The u_{it} represent idiosyncratic errors that change across time and observations (Wooldridge (2002)).

The UEM like any other model can be applied only if certain assumptions hold. The most important and fundamental is the strict exogeneity assumption. This assumption states that explanatory variables are not correlated with idiosyncratic errors in each time period. It can be written as following:

$$E(u_{it}|x_{i1},..,x_{iT},c_i) = 0 \qquad t = 1,2,\dots,T \tag{2}$$

The violation of this assumption is called an endogeneity issue which leads to false statistical inferences and efficiency problems of standard estimators. However, it is possible to test for endogeneity by extracting error terms from a regression and running a correlation analysis between the extracted error terms and regressors. Instrumental variables approach could be another remedy in case of the endogeneity problem (Wooldridge (2002)).

The other cause of endogeneity might be the omitted-variable bias. Although this issue is mitigated by including an individual effect into a regression, it is important to test whether the individual effect is correlated with explanatory variables because it helps to determine which type of UEM should be used. There are four types of UEM widely used in practice: pooled ordinary least squares (POLS), RE model, FE model, and first differencing (FD) model (Baltagi (2005)).

4.3.1 Pooled OLS

The POLS is a standard OLS regression which is run on panel data. This model can only be used when an individual effect is observed for all individuals. The general specification of the model is the following:

$$y_{it} = x_{it}\beta + v_{it} \qquad t = 1,2,\dots,T \tag{3}$$

The individual effect and idiosyncratic errors are combined into the composite errors v_{it} that are the sum of these two components. The POLS regression provides consistent and efficient estimates only when three main assumptions of the model hold (Wooldridge (2002)).

The first assumption of POLS model is that no correlation exists between the explanatory variables x_{it} and the composite errors v_{it}:

$$E(x'_{it}v_{it}) = 0 \qquad t = 1,2,\dots,T \tag{4}$$

However, this assumption is rather restrictive and may not hold because there is a high chance that the social policy of MFIs, which is the individual effect, can affect their SPIs, which are explanatory variables (Wooldridge (2002)).

The second assumption states that explanatory variables are not linearly dependent and thus the POLS estimator matrix must have a full rank:

$$rank[\sum_{t=1}^{T} E(\, x'_{it}\, x_{it})\,] = K \tag{5}$$

The full rank matrix means that it is impossible to replicate one of its rows or columns using a linear transformation of its other rows or columns (Wooldridge (2002)).

The last assumption implies that unconditional variance of the composite error is constant, and the composite errors are not serially correlated:

$$E(v_i v'_i) = \sigma_v^2 \mathrm{I}_T \; and \qquad t = 1,2,\dots,T \tag{6}$$

In conclusion, it is evident that POLS model has very restrictive assumptions that often do not hold in practice and thus this model is rarely applied for panel data analysis. Furthermore, it is important to emphasize that POLS asymptotic qualities can be implemented only for large number of observations and fixed number of time periods (Wooldridge (2002)).

4.3.2 Random Effects Model

The RE model allows the individual effect to be an unobserved random element which is drawn from the sample once per period for each MFI and it enters a regression identically in each period. The possibility of the unobserved effect to be random in each period is indeed a great feature of the RE model because it is difficult to imagine that there is only one MFI-specific indicator that influences a dependent variable throughout all time periods in a sample. However, the RE model imposes more restrictive assumptions than any other model (Greene (2012)).

The general form of this model is described by equation 1. Since the RE method is inconsistent if one or multiple assumptions of the model are violated, it is important to mention them.

The first assumption of RE model is strict exogeneity and orthogonality between unobserved effects and regressors:

$$E(u_{it}|x_i, c_i) = 0, t = 1, \dots, T \quad and \quad E(c_i|x_i) = E(c_i) = 0 \tag{7}$$

The second assumption of a full rank condition is needed because the RE method uses generalized least squares estimator which is only consistent when this assumption holds:

$$rank\, E(X_i' \Omega^{-1} X_i) = K \tag{8}$$

The third assumption states that the conditional variances of the idiosyncratic errors are constant, and the unobserved effects are homoskedastic:

$$E(u_i u_i' | x_i, c_i) = \sigma_u^2 \mathrm{I}_T \quad and \quad E(c_i^2 \big| x_i) = \sigma_c^2 \tag{9}$$

This assumption is very restrictive because the variances of the idiosyncratic errors often change over time and they sometimes demonstrate serial correlation. Fortunately, RE estimator remains consistent even if the third assumption does not hold. However, the RE method requires a feasible generalized least squares estimator when heteroskedasticity or autocorrelation is found in the idiosyncratic errors (Wooldridge (2002)).

4.3.3 Fixed Effects Model

The FE model is more robust than the previous models if the unobserved effect is correlated with the regressors. This approach is based on assumption that individual effect remains constant throughout all periods in a data sample. Although this model allows to consistently estimate the partial effects of regressors on an explanatory variable in the presence of time-invariant omitted variables, it cannot estimate time-constant factors in the explanatory variables. The nature of this drawback lies in the method of estimation. The FE transformation or within transformation eliminates the unobserved effect by first averaging the equation 1 over all time periods in the sample and then subtracting the averaged equation from equation 1:

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)\beta + u_{it} - \bar{u}_i \qquad\qquad t = 1,2, \dots, T \tag{10}$$

The FE model relies on assumptions similar to the RE model, albeit less restrictive. The first assumption is strict exogeneity of the explanatory variables conditional on the individual effect:

$$E(u_{it}|x_i, c_i) = 0, t = 1, 2, \dots, T \tag{11}$$

The second assumption ensures that the FE estimator remains consistent when the number of observations becomes infinitely large:

$$rank(\sum_{t=1}^{T} E(\ddot{x}_{it}' \, \ddot{x}_{it})) = rank\, [E(\ddot{X}_i' \, \ddot{X}_i)] = K \tag{12}$$

The last assumption ensures efficiency of the FE estimator:

$$E(u_i u_i'|x_i, c_i) = \sigma_u^2 \mathrm{I}_T \tag{13}$$

The third assumption requires the homoskedasticity of the idiosyncratic errors and no serial correlation. However, this assumption can be relaxed by using an unrestricted and constant conditional covariance matrix. This extension to the FE method is called FEGLS model (Wooldridge (2002)).

4.3.4 First Differencing Model

The FD model is almost the same as the FE model. The only difference is the method of estimating the effect of regressors on the dependent variable. The FD transformation removes the unobserved effect but loses one time period for each cross section (Wooldridge (2002)). Since the subsample of SPIs is rather small and FD approach is not more efficient than other methods, this model will not be used in this thesis.

4.4 Dependent Variables

The dependent variables in this study are chosen following the methodological approach in the previous research (Gonzalez (2010)). The FP of MFIs is described by three indicators that can be assigned to the following FP categories: profitability, efficiency, and productivity.

4.4.1 Profitability Variable

The most commonly used profitability indicators in the literature are ROA and OSS (e.g. Cull, Demirgüc-Kunt, and Morduch (2007), Quayes (2012), and Martinez (2015)). ROA is defined as net operating income less of taxes divided by average assets. This indicator measures how MFIs manage their assets to optimize profitability. This ratio is net of income taxes and excludes donations and non-operating items (MIX (2018, 7 December 2018)).

Although OSS is also used as profitability indicator, this thesis does not follow this approach. Quayes (2015) argues that OSS is less appropriate than ROA for measuring profitability of MFI. Furthermore, OSS in MIX database is not adjusted by subsidies and donations and thus might misrepresent profitability of MFIs. Lastly, Marr and Awaworyi (2012) claim that OSS must be an indicator of efficiency because it represents an ability of MFIs to cover their operational costs by operating income.

4.4.2 Efficiency Variable

Most of the academic papers on efficiency of MFIs use either OPEXP divided by average total assets or average GLP as efficiency proxy (e.g. Cull, Demirgüc-Kunt, and Morduch (2007), D'espallier, Guerin, and Mersland (2013), and Meyer (2019)). This study chooses to use OPEXP divided by average GLP because this measure is the best representation of costs in relation to core product of MFIs. Some MFIs might have significant parts of their assets invested into non-microfinance activities and thus OPEXP to average total assets may misrepresent the proportion of costs incurred to support core business of MFIs.

4.4.3 Productivity Variable

The productivity measures used by MIX are borrowers per staff member and depositors per staff member. Both measures help to assess productivity of MFI’s employees (MIX (2018, 7 December 2018)). However, some MFIs do not have any depositors and some of them have more depositors than borrowers. Thus, the best approach is to combine both productivity indicators into a new productivity indicator which is called clients per staff member.

4.5 Independent Variables

All independent variables in this study describe SP of MFIs. The standard proxies for SP are chosen based on the previous literature. The alternative indicators of SP are chosen based on the study by Bédécarrats, Baur, and Lapenu (2012).

The original SPI tool was updated in 2014 and renamed to SPI4. The CERISE SPI4 was combined with the Universal Standards for Social Performance Management developed by SPTF. The upgraded tool contains six core dimensions for MFIs with a double bottom line objective and one optional seventh dimension for MFIs pursuing triple bottom line (CERISE (2018, 7 December 2018)). Unfortunately, MIX started collecting the data based on upgraded

SPI4 only after 2014 and thus this thesis uses the old version of SPI4 with only four dimensions.

4.5.1 Standard Variables

The standard proxies used for SP in many academic papers are ALB and FEMALE.

Average Loan Balance

The ALB oftentimes divided by local GNI per capita is believed to be an indicator of depth of outreach. The best and most intuitive approach of measuring depth of outreach would be to assess personal wealth of each individual borrower and investigate whether MFIs provide loans to borrowers with very little or no wealth (Louis, Seret, and Baesens (2013)). However, this approach would be prohibitively costly, and borrowers may not want to share this kind of information. Thus, the only remaining option is to use ALB and assume that lower values of this variable should indicate lower wealth levels of borrowers.

Although ALB as percentage of GNI per capita is used by many researchers, it is important to emphasize that this measure has some pitfalls. First, the assumption that ALB indicates client poverty level has been tested only by a few studies (Goedecke, D'Espallier, and Mersland (2016)). One of them finds little correlation between poverty score cards and ALB based on the client data from a Bosnian MFI (Schreiner et al. (2014)). Second, growing MFIs often expand their customer base to slightly less poor clients without reducing a number of the very poor clients served. Thus, ALB increases due to an additional client group (Goedecke, D'Espallier, and Mersland (2016)). Third, a size of loan always depends on borrowers' activities. Some clients take loans for purchase of assets and others need them for consumption. Consequently, different borrowers request different sizes of loans (Morduch (2000)). Obviously, ALB cannot reflect these peculiarities (Goedecke, D'Espallier, and Mersland (2016)). Fourth, ALB is not very usable because it lacks information on the distribution of loan sizes among borrowers. More informative indicator would include kurtosis and skewness of loans distribution and therefore allow researchers to perform more sophisticated analysis. Lastly, there is no universal definition of ALB measurement. Normally ALB is calculated as average GLP divided by average total number of active borrowers (MIX (2018, 7 December 2018)). However, this measure can be also calculated taking such factors as term to maturity, amount of instalment, or time between instalments into account (Schreiner (2002)). Thus, comparability of this measure might be an issue (Goedecke, D'Espallier, and Mersland (2016)).

Percentage of Female Borrowers

The FEMALE is considered to be a very significant measure of SP for three reasons. First, focus on women is believed to facilitate women's empowerment. Microfinance is supposed to increase women's bargaining power within household, control over income and monetary income by helping female entrepreneurs to build or expand commercial activities. Second, some papers claim that women dedicate a larger part of their income to well-being of their families compared to men (D'espallier, Guerin, and Mersland (2013)). Demirguc-Kunt, Honohan, and Beck (2007) show empirically that a loan to female borrower appears to have greater impact on development than a loan to a male borrower. Third, targeting women is associated with high repayment rates and significant contribution to economic growth (Mayoux (2001)).

However, the FEMALE is often used only as a complementary measure of SP, since it is often inversely correlated with ALB. Many academic papers include it to reinforce the assumption that more female borrowers are associated with smaller loans and thus better SP (D'espallier, Guerin, and Mersland (2013)). Thus, it is not clear whether this measure is indeed a good indicator of SP.

4.5.2 First Dimension: Targeting and Outreach

The SP measures in this dimension assess the level of outreach to the poor and excluded populations. Since this dimension is characterised by three criteria, various SP variables are used to match each criterion.

Geographic Targeting

The most appropriate proxy for "Geographic targeting" would be a number of offices. This variable was already used in the other paper (Marr and Awaworyi (2012)). Furthermore, Schreiner (2002) argues that one of the six aspects of outreach is "Cost of outreach to clients". One part of this aspect is indirect cash expenses for transportation. These expenses can be minimized if MFI's office is close to borrowers and thus the number of offices is a good variable for SP.

Individual Targeting

The best proxy for this criterion would be a poverty target which has four poverty levels. However, this measure has very few observations in the data sample and thus it cannot be used. The second-best choice would be a number of active female borrowers, but this proxy is a standard measure of SP. In the absence of any better measures, a number of rural clients is used as an indicator of individual targeting. This proxy was also indicated as a simple, indirect measure of depth of outreach by Schreiner (2002). Lastly, Krauss and Meyer (2018) consider the number of rural clients a good SP indicator, but do not include it into their SP measurement tool due to insufficient number of observations.

Methodological Targeting

The best-choice indicator for this criterion in the data sample would be a poverty reduction objective which is an ordinal variable with ten ranks indicating the importance of this objective for MFI with one being the highest rank (MIX (2018, 7 December 2018)). However, it is not used in this paper due to insufficient number of observations. Therefore, the third criterion of the first dimension is not included into empirical analysis.

4.5.3 Second Dimension: Adaption of Services

The SP measures in this dimension evaluate how well financial products provided by MFIs satisfy clients' needs. Since this dimension is characterised by three criteria, various SP variables are used to match each criterion.

Range of Traditional Services

The most common complementary service to lending is saving. Thus, the presence of information on deposits volume is used to proxy for range of services. This proxy is a binary variable with one meaning that MFIs take deposits from their clients and zero indicating that they do not mobilise deposits. This measure of SP is also discussed by Schreiner (2002) and he believes that it is a good indicator of scope of outreach. Moreover, Krauss and Meyer (2018) consider a number of depositors served a good SP indicator and include it into their SP measurement tool.

Quality of Services

The most appropriate proxy for this criterion would be a client retention rate. However, the only available variable in the dataset is a borrowers retention rate. This SP measure is believed to measure the satisfaction of borrowers, but it has several pitfalls. First, some clients simply do not have a choice and therefore they keep coming for new loans even if quality of service is bad. Second, some borrowers may want to wait for a certain time before applying for a new loan. Although quality of service remains the same, such clients lead to the decreasing borrowers retention rate (CGAP (2006b, 22 December 2018)). Despite these drawbacks the borrowers retention rate is considered a good measure for SP (Krauss and Meyer (2018)).

Innovative and Non-Financial Services

The best measures of this aspect of SP in the data sample would be binary variables indicating whether MFIs offer enterprise, education, and health services. However, none of them are used in this thesis due to insufficient number of observations. Therefore, the third criterion of the second dimension is not included into empirical analysis.

4.5.4 Third Dimension: Benefits to Clients

The SP indicators in this dimension measure economic and social benefits to the clients created by financial services. Since this dimension is characterised by three criteria, various SP variables are used to match each criterion.

Economic Benefits

This criterion can be also described as worth of financial services to clients (Schreiner (2002)). Since poor borrowers often have a choice between multiple financial service providers described in the chapter “The Current State of Microfinance”, they choose to use the services of MFIs only if they represent the best option. Alternatively, the borrowers can forgo borrowing if they believe that it will not benefit them. Thus, the best available proxy for economic benefits to the borrowers is a number of new borrowers during period.

Client Participation

The best measures of this indicator would be a categorical variable that describes level of client involvement. However, there is no such measure in the data sample. Thus, the second criterion of the third dimension is not included into empirical analysis.

Client Empowerment

The most appropriate proxy for this SP measure in the data sample would be a binary variable indicating whether MFIs offer women empowerment services. However, it is not used in this study due to insufficient number of observations. Therefore, the third criterion of the third dimension is not included into empirical analysis.

4.5.5 Fourth Dimension: Social Responsibility

The SP indicators in this dimension evaluate the level of SR of MFIs towards their stakeholders. Since this dimension is characterised by three criteria, various SP variables are used to match each criterion.

SR to Employees

The best indicator for this aspect of SP would be a categorical variable that contains various employee protection principles. However, this variable has insufficient observations. Thus, this thesis uses a staff turnover ratio as a proxy for SR towards employees. This choice is intuitive because employees usually leave MFIs due to hostile working environment or poor working conditions which are the components of SR.

SR to Clients

The best measures of this aspect of SR in the data sample would be binary variables that indicate if certain client protection processes and policies are implemented. However, these variables have extremely low number of observations. Thus, the second criterion of the fourth dimension is not included into empirical analysis.

SR to the Community and the Environment

The most appropriate proxy for this SR measure in the data sample would be a categorical variable that describes environmentally friendly products financed by MFIs. However, it is not used in this study due to insufficient number of observations. Therefore, the last criterion of the fourth dimension is not included into empirical analysis.

In conclusion, it is worth summarizing all measures and dimensions of SP.

Table 1: Description of SP Measures

Name of dimension	**Description**
Standard variables	
Average loan balance	Average outstanding loan balance compared to local GNI per capita.
Percentage of female borrowers	Number of active female borrowers as a percentage of total borrowers at period end.
Targeting and outreach	
Geographic targeting	Assessment whether MFIs operate in remote areas which are close to the poor in terms of physical distance measured by number of offices.

Individual targeting	Assessment if MFI caters to particular groups of poor clients measured by number of rural clients.
Methodological targeting	Analysis if products and services offered by MFIs target poor or excluded customers measured by poverty reduction objective. This measure is not used in this thesis due to insufficient number of observations.
Adaption of services	
Range of traditional services	Evaluation whether MFIs offer only lending or also any other types of financial services measured by dummy variable that defines whether MFIs mobilise deposits.
Quality of services	Assessment of the quality of financial services provided by MFIs measured by borrowers retention rate.
Innovative and non-financial services	Evaluation whether MFIs offer any unconventional and non-financial services measured by dummies that evaluate if MFIs offer enterprise, education, and health services. This measure is not used in this thesis due to insufficient number of observations.
Benefits to clients	
Economic benefits to the clients	Evaluation whether financial services offered by MFIs improve socioeconomic status of their clients measured by number of new borrowers.
Client Participation	Analysis whether clients are involved in governance of MFIs measured by level of client involvement. This measure is not used in this thesis because it is not present in dataset.
Client empowerment	Analysis whether MFIs contribute to the empowerment and social capital building of their clients measured by women empowerment services. This measure is not used in this thesis due to insufficient number of observations.
Social responsibility	

SR to employees	Evaluation whether MFIs are socially responsible towards their employees measured by staff turnover ratio.
SR to clients	Assessment whether MFIs follow client protection principles measured by binary variable that indicates whether certain client protection processes and policies are implemented. This measure is not used in this thesis due to insufficient number of observations.
SR to the community and the environment	Assessment whether MFIs contribute to the improvement of local environment measured by environmentally friendly products financed by MFIs. This measure is not used in this thesis due to insufficient number of observations.

Source: Bédécarrats, Baur, and Lapenu (2012) and MIX (2018)

4.6 Control Variables

The control variables are included in all regressions to increase robustness of the empirical results. This thesis uses three control variables: total assets, portfolio at risk past 30 days, and legal status.

4.6.1 Total Assets

The total assets indicator is a proxy used for size of MFIs in many studies (e.g. D'espallier, Guerin, and Mersland (2013), Kar (2013), and Périlleux and Szafarz (2016)). This proxy is defined as aggregated value of resources controlled by MFIs as a consequence of past events and from which future economic benefits are expected to be generated. It is calculated as a sum of each individual asset account listed on balance sheet of MFIs (MIX (2018, 7 December 2018)).

The size measure also partly controls for the age of MFIs. Most mature MFIs have larger total assets than the young or new ones. Moreover, the age of MFI variable reported in the dataset does not indicate number of years since foundation, but it is a categorical variable that has three classes. Thus, the age variable is not included into empirical analysis due to interpretability concerns.

4.6.2 Portfolio at Risk

The portfolio at risk is a standard measure of portfolio quality. Since most of loans in microfinance have very short tenor, the most widely used breakpoint is 30 days. This indicator reflects the risk related to non-repayment of loans and helps to assess future revenues (Bassem (2012)). The portfolio at risk past 30 days represents the share of GLP which is past due more than 30 days and it also includes the value of all renegotiated loans (MIX (2018, 7 December 2018)).

4.6.3 Legal Status

Some research papers use legal status of MFIs to control for structural attributes of MFIs (e.g. Louis, Seret, and Baesens (2013), D'espallier, Guerin, and Mersland (2013), and Meyer (2019)). This research follows this approach because banks pursue different goals compared to NGOs and thus it is important to take this fact into account.

4.7 Hypotheses

The hypotheses in this section describe predicted relation between FP and SP measures of MFIs. The hypotheses for standard SP variables are based on previous research and the hypotheses of some alternative SP variables are developed based on author's opinion.

4.7.1 Standard Model Hypotheses

As described in the previous chapter the standard measures of SP describe outreach to poor populations and they are measured by ALB divided by average GNI per capita and FEMALE.

The first hypothesis is based on the findings of Bassem (2012) and Meyer (2019) regarding the relation between SP and ROA. Both papers find that SP does not have any significant effect on FP. Thus, the hypothesis 1.1 assumes a neutral relation between FP and profitability:

Hypothesis 1.1: Smaller loans and higher focus on women have a neutral impact on profitability.

The second hypothesis reflects the results from the studies of Hermes, Lensink, and Meesters (2011) and D'espallier, Guerin, and Mersland (2013). Both studies find that smaller loans and focus on women are associated with higher operating costs due to increased monitoring effort and administrative expenses. These findings are reflected in the hypothesis 1.2:

Hypothesis 1.2: Smaller loans and higher focus on women have a negative impact on efficiency.

The third hypothesis is derived from the findings in the paper published by Gonzalez (2010) and theoretical arguments from Armendáriz and Morduch (2005). Since women are on average poorer than men, they request smaller loans. Smaller loans are delivered faster than larger loans because most MFIs offer small loans through the group lending methodology, whereas large loans are normally delivered through individual lending. The group lending is safer than individual lending, since group members act as guarantors for each other and thus time and effort for credit analysis of borrowers in a group is lower compared to individual lending. In conclusion, smaller loans that are correlated with a large number of female borrowers are expected to increase a number of borrowers per staff member:

Hypothesis 1.3: Smaller loans and higher focus on women have a positive impact on productivity.

4.7.2 Targeting and Outreach Model Hypotheses

As already mentioned in the previous chapter targeting and outreach dimension describes level of outreach to the poor and it is measured by the number of offices and rural clients.

The first hypothesis is postulated based on the trade-off between additional costs and revenues from further extension of offices network and increase in number of rural clients. A large number of offices increases staff size and administration expenses. However, extensive network of offices helps MFIs to reach more customers and consequently generates more revenue. Rural clients are on average less educated than urban clients and thus might not be willing to use mobile banking services. Therefore, they require physical points of service and thus contribute to additional costs. Nevertheless, they represent less risky borrowers than urban clients due to their reduced social mobility and increased social capital (Armendáriz and Morduch (2005) and Postelnicu and Hermes (2016)). Therefore, the hypothesis 2.1 predicts a neutral relation between SP and profitability:

Hypothesis 2.1: Greater number of offices and rural clients have a neutral impact on profitability.

The second hypothesis is already partly included in the previous one. The higher number of offices as well as rural clients should lead to increased costs.

Hypothesis 2.2: Greater number of offices and rural clients have a negative impact on efficiency.

The third hypothesis includes the finding from the literature that geographic targeting is positively related to a number of borrowers per staff member (Bédécarrats, Baur, and Lapenu (2012)).

Hypothesis 2.3: Greater number of offices and rural clients have a positive impact on productivity.

4.7.3 Adaption of Services Model Hypotheses

As already reported in the previous chapter adaption of services dimension evaluates how well financial products provided by MFIs satisfy clients' needs and it is measured by a dummy variable that defines whether MFIs mobilise deposits and a borrowers retention rate.

The first hypothesis is based on the funding choices which MFIs face before they turn to deposits and trade-off between costs and revenues generated by a greater number of borrowers. First, the MFIs that have access to subsidized funding and donations always experience lower funding costs than MFIs that rely only on deposits. On the other hand, some MFIs do not receive any funding from sponsors and thus they must borrow funds from other financial institutions or tap capital markets which is usually a more expensive option than mobilisation of deposits. Thus, only the latter MFIs have an incentive to offer deposit services to their clients and therefore lower their financing costs. Second, according to the findings of Bédécarrats, Baur, and Lapenu (2012) the higher client retention rate results in decreased operating costs. Thus, the hypothesis 3.1 is formulated as following:

Hypothesis 3.1: Higher borrowers retention rate and presence of savings products have a positive impact on profitability.

The second hypothesis is derived from the first one. The higher borrowers retention rate should lead to decrease in operational expenses because the returning borrowers are already familiar with mechanics of lending process and thus require less time of MFI's staff. Although a higher volume of deposits lowers funding costs for MFIs, it can contribute to increase in OPEXP due to additional effort that must be allocated to service of depositors.

Hypothesis 3.2: Higher borrowers retention rate and absence of savings products have a positive impact on efficiency.

The third hypothesis is based on the findings by Gonzalez (2010). He reports that MFIs with higher dropout rates are associated with lower productivity. The presence of depositors has an unclear link to productivity.

Hypothesis 3.3: Higher borrowers retention rate has a positive impact on productivity, whereas presence of savings products has a neutral impact on productivity.

4.7.4 Benefits to Clients Model Hypotheses

As already outlined in the previous chapter the benefits to clients dimension estimates economic and social benefits to clients created by financial services and it is measured by a number of new borrowers.

The first hypothesis is based on the trade-off between costs and revenues generated by new borrowers. It is extremely difficult to predict whether new clients contribute to profitability because MFIs pursue a double bottom line objective and thus may be willing to continue expanding their customer base even if it is not profitable for them. Thus, the hypothesis 4.1 predicts a neutral link between a number of new borrowers and profitability.

Hypothesis 4.1: Greater number of new borrowers has a neutral impact on profitability.

The second hypothesis reflects the fact that more borrowers require more time and assistance from staff members and thus cause increased OPEXP.

Hypothesis 4.2: Greater number of new borrowers has a negative impact on efficiency.

The third hypothesis assumes that a natural response to increased number of clients would be increase in productivity or a number of staff members. Since many MFIs and clients have already embraced mobile banking as discussed in the section “The Current State of Microfinance”, the increase in productivity seems to be a more preferred option. Thus, the hypothesis 4.3 predicts that a higher number of clients results in higher productivity.

Hypothesis 4.3: Greater number of new borrowers has a positive impact on productivity.

4.7.5 Social Responsibility Model Hypotheses

As already explained in the previous chapter SR dimension investigates level of SR of MFIs towards their stakeholders and it is measured by a staff turnover ratio.

The first hypothesis considers the fact that new employees, that substitute the ones who left, require proper training and certain time before they can serve clients. Consequently, this leads to increased costs and decreased revenues for MFIs.

Hypothesis 5.1: Lower staff turnover ratio has a positive impact on profitability.

The second hypothesis reflects the fact that an additional training that must be provided to new recruits causes additional OPEXP.

Hypothesis 5.2: Lower staff turnover ratio has a positive impact on efficiency.

The third hypothesis is postulated based on the fact that in the beginning new employees are always less productive than current ones, since they must be trained before starting their work.

Hypothesis 5.3: Lower staff turnover ratio has a positive impact on productivity.

5 Empirical Results

This section presents and discusses the empirical findings of the thesis. At first, the specification of each model is given. Second, the descriptive statistics are demonstrated. The full summary of variables can be found in Table 21 from Appendix A. The data preparation process for empirical analysis is described in Appendix B. Third, the results of empirical analysis are illustrated. Fourth, the robustness tests are performed, and possible endogeneity issues are examined. In the end, the empirical results are summarized.

5.1 Standard Model

The standard model includes FP measures as dependent variables and ALB divided by GNI per capita and FEMALE as independent variables. The MFI-specific controls are also added to ensure robustness of the model. Since this model utilises the SP variables commonly used in previous studies, it serves as a reference point for later comparison with other models. The specification of the standard model is the following:

$$ROA_{it}/OPEXGLP_{it}/CLIENTSTAFF\_LN_{it} = \beta_0 + \beta_1 ALBGNI_{it} + \beta_2 FEMALE_{it} + \beta_3 SIZE\_LN_{it} + \beta_4 PAR30_{it} + \beta_{5-9} LEGAL_{it} + v_{it} \tag{14}$$

The detailed description of all variables is provided in Table 21 in Appendix A. The CLIENTSSTAFF and SIZE variables are log-transformed to improve interpretability of results. The class “Bank” in a categorical variable LEGAL is a baseline and thus omitted from the regression. The term v_{it} represents composite errors discussed in the chapter “Research Method”.

5.1.1 Descriptive Statistics

Table 2 demonstrates different statistical metrics of the data subsample used for the standard model. The subsample represents an unbalanced panel which contains 7’299 year-MFI observations of 1’515 MFIs from 1997 until 2014. The average diamonds ranking of the MFIs in this data subsample is 3.85 what indicates good quality of the data. Most of the MFIs in the subsample are regulated. The most common legal form of MFIs in the subsample is either NGO or NBFI. This finding indicates that NGOs and NBFIs might be more willing to report standard SP measures than all other legal forms.

With respect to FP, the average ROA is 1.96% meaning that the MFIs in the subsample are generating profits.

The SP measures show that the ALBGNI ratio is 60% indicating that MFIs from the subsample offer slightly smaller loans than their peers from the overall sample presented in Table 23 Appendix B. The MFIs in the subsample have 64% female borrowers like MFIs in the overall sample.

Table 2: Standard Model Descriptive Statistics

Variable	Obs.	Mean	SD	Min	Max
General variables					
YEAR	7298	2008	3	1997	2014
DIAMOND	7298	3.85	0.78	1.00	5.00
REGULATED	7298	61.78%	48.60%	0.00%	100.00%
Dependent variables					
ROA	7298	1.96%	8.54%	-95.63%	100.89%
OPEXPGLP	7298	25.46%	18.02%	1.00%	99.74%
CLIENTSSTAFF	7298	216	174	3	999
Independent variables					
ALBGNI	7298	59.87%	88.10%	1.08%	990.09%
FEMALE	7298	63.93%	25.79%	0.00%	100.00%
Control variables					
SIZE (in $m)	7298	43.51	147.07	0.00	2930.00
PAR30	7298	6.42%	9.35%	0.01%	99.20%
LEGAL:					
Bank	111				
Credit Union / Cooperative	304				
NBFI	483				
NGO	502				
Other	20				
Rural Bank	95				
Total	1515				

Source: own calculation

5.1.2 Multicollinearity test

Table 3 shows the correlation matrix. The correlation analysis is important because it helps to identify a multicollinearity issue. The multicollinearity problem is defined as perfect correlation between two explanatory variables and it leads to infinite variance of predictors.

The symptoms of multicollinearity are very high standard errors of coefficients and low significance levels, “wrong” signs or implausible magnitudes of coefficients, and wide swings in parameter estimates due to small changes in data (Greene (2012)).

Table 3 clearly demonstrates that the pairwise Pearson correlations between regressors are not in the area of 0.8 to 0.9 and thus no collinearity among two variables can be detected (Kennedy (2008)). The correlation matrix exhibits nearly neutral correlation between profitability and standard measures of SP as predicted by the first hypothesis. The negative correlation between ALBGNI and operating costs as well as positive correlation between FEMALE and operating costs are in line with the second hypothesis. The negative correlation between ALBGNI and productivity contradicts the third hypothesis. Lastly, the correlation analysis demonstrates negative correlation between ALBGNI and FEMALE what could be considered as evidence that female borrowers request smaller loans.

Table 3: Standard Model Correlation Matrix

		1	*2*	*3*	*4*	*5*	*6*	*7*
1	ROA	1						
2	OPEXPGLP	-0.32	1					
3	CLIENTSSTAFF	0.03	-0.16	1				
4	ALBGNI	0.02	-0.18	-0.11	1			
5	FEMALE	0.01	0.19	0.16	-0.38	1		
6	SIZE	0.03	-0.16	0.16	0.08	-0.07	1	
7	PAR30	-0.28	0.08	-0.02	0.03	-0.10	-0.02	1

Source: own calculation

5.1.3 Regression Results

The first step in regression analysis is to check whether there is the unobserved effect in the composite error discussed in the section “Research Method”. The absence of such effect is a precondition for the POLS method. The best way to check for this effect is to run “Wooldridge's test for unobserved individual effects” (Croissant and Giovanni (2008)). The null hypothesis of this test states that there is no unobserved effect in the composite error (Wooldridge (2002)). The result of the test which is not reported in this study shows very low p-value and thus leads to rejection of the null hypothesis on all significance levels. Consequently, the POLS approach cannot be used.

The next step is to run the FE and RE models for each dependent variable and use “Hausman test” to check which model is more appropriate (Croissant and Giovanni (2008)). The null hypothesis of this test states that there is no misspecification and therefore both models are consistent (Hausman (1978)). The results of the test which are not reported in this thesis indicate very low p-value and thus lead to rejection of the null hypothesis on all significance levels. Thus, the RE method is not appropriate.

It is important to test whether the third assumption of constant variation and no autocorrelation in error terms described in the chapter “Fixed Effects Model” still holds before making any statistical inferences. First, the tests for heteroskedasticity of the error terms are performed. The null hypothesis of these tests states that the error terms have constant variance and thus homoscedastic (Breusch and Pagan (1979)). The results of the tests which are not reported in this paper indicate very low p-value and thus lead to rejection of the null hypothesis on all significance levels. Second, the tests for serial correlation are performed. The null hypothesis of these tests states that there is no serial correlation in the idiosyncratic errors (Breusch and Pagan (1980)). The results of the tests which are not reported in this paper indicate very low p-value and thus lead to rejection of the null hypothesis on all significance levels.

Therefore, the heteroskedastic error terms and evidence of serial correlation in the idiosyncratic errors require FEGLS method to improve efficiency of estimator.

Table 4 presents the results of the FEGLS regressions.

The results of the profitability regression indicate that smaller loans have negative effect on profitability. This finding seems to be in line with notion that smaller loans are associated with higher operating costs due to increased monitoring effort and administrative expenses. It seems that more female borrowers contribute to higher profitability of MFIs which is a contradiction to most of the previous literature on this topic. This finding might be a result of a higher repayment rate associated with focus on women examined by D'espallier, Guerin, and Mersland (2013). Thus, hypothesis 1.1, which predicts that smaller loans and higher focus on women have a neutral effect on profitability, is not supported by the data. Both control variables are significant at 1% significance level indicating that larger MFIs with less risky loan portfolios are more profitable.

The results of the efficiency regression fully support hypothesis 1.2, which assumes that smaller loans and higher focus on women have a negative impact on efficiency. Both control variables are significant at 1% significance level demonstrating that larger MFIs with less risky loan portfolios can achieve economies of scale and therefore lower their costs.

The results of the productivity regression fully support hypothesis 1.3, which anticipates that smaller loans and higher focus on women have a positive impact on productivity. Both control variables are significant at 1% significance level showing that larger MFIs with less risky loan portfolios are more productive.

Lastly, Multiple R-squared for all regressions are quite high indicating that the models fit to the data quite well.

Table 4: Standard Model FEGLS Regression Results

	ROA	OPEXPGLP	CLIENTSSTAF_LN
ALBGNI	0.0096***	-0.0105***	-0.3528***
	(0.0006)	(0.0008)	(0.0072)
FEMALE	0.0253***	0.0246*	0.1201***
	(0.0054)	(0.0060)	(0.0280)
SIZE_LN	0.0150***	-0.0395***	0.0606***
	(0.0005)	(0.0007)	(0.0038)
PAR30	-0.2269***	0.0250***	0.0137***
	(0.0079)	(0.0091)	(0.0467)
Observations	7298	7298	7298
Multiple R-squared	0.634	0.854	0.869

Significance codes: *** 1% level, ** 5% level, * 10% level

Source: own calculation

5.1.4 Robustness Check

The last remaining assumption of UEM described in the section "Research Method" is the strict exogeneity assumption. The violation of this assumption is called an endogeneity issue. This problem often arises when some omitted variables are correlated with both dependent and explanatory variables and thus lead to biased regression results (Baltagi (2005)). For instance, some global industry trends such as globalisation or financial crisis influence FP as well as SP of MFIs. Thus, it becomes difficult to estimate the unique impact of SP indicators on FP measures. Although this problem is partly mitigated by introducing an unobserved effect on individual level of MFIs, it is still important to test for a possibility of omitted-variable bias.

The most intuitive test for endogeneity issue would be to extract error terms from the regressions and conduct a correlation analysis between the extracted error terms and regressors. Tables 24-26 in Appendix C illustrate the results of endogeneity test. The correlation values between the regressors and error terms are close to zero indicating absence of endogeneity issue.

One additional source of endogeneity may be a self-selection bias (Wooldridge (2002)). The self-selection bias arises when some MFIs choose not to report standard SP variables because they are below average. Thus, the data sample contains only top social performers that may also have above average FP. Consequently, the empirical results of standard model are not valid for MFIs that do not report SP measures. However, comparison of Table 2 and Table 23 in Appendix B clearly shows that average FP indicators in both data samples ae very similar. Thus, the self-selection bias is not an issue in the standard model.

5.2 Targeting and Outreach Model

The targeting and outreach model includes FP measures as dependent variables and standard measures of SP as well as number of offices and rural clients as independent variables. The MFI-specific controls are also added to ensure robustness of the model. The specification of targeting and outreach model is the following:

$$ROA_{it}/OPEXGLP_{it}/CLIENTSTAFF\_LN_{it} = \beta_0 + \beta_1 ALBGNI_{it} + \beta_2 FEMALE_{it} + \beta_3 OFFICES\_LN_{it} + \beta_4 RURAL_{it} + \beta_5 SIZE\_LN_{it} + \beta_6 PAR30_{it} + \beta_{7-11} LEGAL_{it} + v_{it} \tag{15}$$

The detailed description of all variables is provided in Table 21 in Appendix A.

5.2.1 Descriptive Statistics

Table 5 demonstrates different statistical metrics of the data subsample used for the targeting and outreach model. The sample represents an unbalanced panel which contains 2’845 year-MFI observations of 1’038 MFIs from 2005 until 2013. This subsample is significantly smaller in comparison to the previous model. All general variables are similar to the previous model.

The FP variables are almost identical to the previous model.

The SP measures show that the ALBGNI is 52.67% which is slightly lower compared to the previous model. The average number of offices operated by MFIs is higher compared to the overall sample presented in Table 23 in Appendix B. The percentage of rural clients served by MFIs is very similar to the overall sample.

Table 5: Targeting and Outreach Model Descriptive Statistics

Variable	Obs.	Mean	SD	Min	Max
General variables					
YEAR	2845	2010	2	2005	2013

DIAMOND	2845	3.95	0.62	1.00	5.00
REGULATED	2845	63.13%	48.25%	0.00%	100.00%
Dependent variables					
ROA	2845	1.96%	7.32%	-63.54%	59.98%
OPEXPGLP	2845	22.75%	15.77%	1.15%	99.37%
CLIENTSSTAFF	2845	214	172	4	984
Independent variables					
ALBGNI	2845	52.67%	72.95%	1.61%	990.09%
FEMALE	2845	64.03%	25.35%	0.00%	100.00%
OFFICES	2845	53	194	1	3304
RURAL	2845	53.89%	32.37%	0.00%	100.00%
Control variables					
SIZE (in $m)	2845	56.18	163.22	0.08	2930.00
PAR30	2845	6.56%	9.84%	0.01%	99.20%
LEGAL:					
Bank	77				
Credit Union / Cooperative	179				
NBFI	359				
NGO	355				
Other	14				
Rural Bank	54				
Total	1038				

Source: own calculation

5.2.2 Multicollinearity test

Table 6 shows the correlation matrix. The pairwise Pearson correlations between regressors are not in the area of 0.8 to 0.9 and thus no collinearity among two variables can be detected (Kennedy (2008)).

The correlation analysis demonstrates similar correlations between dependent variables and ALBGNI and FEMALE compared to the previous model. The correlations between main targeting and outreach model variables and dependent variables are all in line with three hypotheses.

Table 6: Targeting and Outreach Model Correlation Matrix

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1	ROA	1								
2	OPEXPGLP	-0.31	1							
3	CLIENTSSTAFF	0.01	-0.20	1						
4	ALBGNI	0.01	-0.15	-0.10	1					
5	FEMALE	-0.02	0.15	0.21	-0.41	1				
6	OFFICES	0.01	-0.11	0.17	-0.06	0.16	1			

7	RURAL	0.02	-0.14	0.14	-0.11	0.13	0.11	1		
8	SIZE	0.04	-0.17	0.16	0.14	-0.09	0.41	-0.06	1	
9	PAR30	-0.28	0.01	-0.01	0.02	-0.09	0.07	0.00	-0.01	1

Source: own calculation

5.2.3 Regression Results

Table 7 presents the results of the FEGLS regressions.

The results of the profitability regression indicate that smaller loans have a positive impact on profitability which is similar to the finding by Quayes (2015). More female borrowers have a positive impact on profitability which is similar to the previous model. Both results indicate that depth of outreach increases profitability of MFIs. The increasing number of offices seems to have a negative impact on profitability. This finding supports the notion that additional costs from extension of offices network are greater than additional revenue. The rurality of the clients seems to have no effect on profitability. Thus, hypothesis 2.1, which proclaims that greater number of offices and rural clients have a neutral effect on profitability, is partly rejected by the data. Both control variables are significant at 1% significance level indicating that larger MFIs with less risky loan portfolios are more profitable.

The results of the efficiency regression demonstrate that the size of loans and number of female borrower have no significant effect on efficiency. The more extensive offices network seems to have a negative impact on efficiency. The increase in the percentage of rural clients is associated with lower costs. Thus, hypothesis 2.2, which predicts that greater number of offices and rural clients have a negative effect on efficiency, is partly supported by the data. Both control variables are significant at 1% significance level demonstrating that larger MFIs with less risky loan portfolios can achieve economies of scale and therefore lower their costs.

The productivity regression reinforces the notion that smaller loans and more female borrowers have a positive impact on productivity. The greater number of offices seems to decrease productivity. However, this finding may also indicate that new offices attract very few clients during the first years after the opening and thus lower the overall number of clients per staff member. The rurality of clients has no statistically significant effect on productivity. Thus, hypothesis 2.3, which states that greater number of offices and rural clients have a positive effect on productivity, is not supported by the data. Only the SIZE control variable is statistically significant showing that larger MFIs are more productive.

Lastly, Multiple R-squared values for all regressions are higher in comparison to the standard model indicating that this model has an additional explanatory power.

Table 7: Targeting and Outreach Model FEGLS Regression Results

	ROA	OPEXPGLP	CLIENTSSTAF_LN
ALBGNI	-0.0137***	-0.0034	-0.2884***
	(0.0030)	(0.0043)	(0.0214)
FEMALE	0.0320***	0.0196	0.2001***
	(0.0105)	(0.0140)	(0.0671)
OFFICES_LN	-0.0121***	0.0271***	-0.0911***
	(0.0017)	(0.0028)	(0.0148)
RURAL	0.0048	-0.0238***	0.0183
	(0.0047)	(0.0065)	(0.0336)
SIZE_LN	0.0223***	-0.0560***	0.1713***
	(0.0015)	(0.0022)	(0.0123)
PAR30	-0.2838***	-0.0427***	0.0052
	(0.0112)	(0.0157)	(0.0752)
Observations	2845	2845	2845
Multiple R-squared	0.735	0.923	0.942
Significance codes: *** 1% level, ** 5% level, * 10% level			

Source: own calculation

5.2.4 Robustness Check

Tables 27-29 in Appendix C illustrate the results of endogeneity test. The correlation values between the regressors and error terms are close to zero indicating absence of the endogeneity issue. However, it is important to check if the self-selection bias may be a problem for targeting and outreach model. As argued by Goedecke, D'Espallier, and Mersland (2016) the MFIs with good SP are more willing to follow up or report rurality or their clients compared to poor social performers. However, the comparison of Table 5 and Table 23 in Appendix B indicates that the first dimension SP and FP variables have similar values in both samples. Thus, the self-selection bias is not an issue in targeting and outreach model.

5.3 Adaption of Services Model

The adaption of services model includes FP measures as dependent variables and standard measures of SP as well as a dummy variable that defines whether MFIs mobilise deposits and a borrowers retention rate as independent variables. The MFI-specific controls are also added to ensure robustness of the model. The specification of the adaption of services model is the following:

$$ROA_{it}/OPEXGLP_{it}/CLIENTSTAFF\_LN_{it} = \beta_0 + \beta_1 ALBGNI_{it} + \beta_2 FEMALE_{it} + \beta_3 DEPOSITS_{it} + \beta_4 BORROWERRETRATE_{it} + \beta_5 SIZE\_LN_{it} + \beta_6 PAR30_{it} + \quad (16)$$

$\beta_{7-11}LEGAL_{it} + v_{it}$

The detailed description of all variables is provided in Table 21 in Appendix A.

5.3.1 Descriptive Statistics

Table 8 demonstrates different statistical metrics of the data subsample used for the adaption of services model. The sample represents an unbalanced panel which contains 1’550 year-MFI observations of 719 MFIs from 2008 until 2014. The sample is significantly smaller compared to the previous model. The MFIs in this subsample are significantly larger and less risky than their peers from the previous model.

The average ROA is significantly higher compared to the previous model. The average MFI from this subsample is significantly less productive than its peers in the previous model.

The percentage of MFIs that mobilise deposits and the number of borrowers that stay with MFIs are similar to the overall sample presented in Table 23 in Appendix B.

Table 8: Adaption of Services Model Descriptive Statistics

Variable	Obs.	Mean	SD	Min	Max
General variables					
YEAR	1550	2012	1	2008	2014
DIAMOND	1550	3.94	0.69	1.00	5.00
REGULATED	1550	62.77%	48.36%	0.00%	100.00%
Dependent variables					
ROA	1550	2.30%	6.95%	-63.54%	45.31%
OPEXPGLP	1550	22.91%	14.87%	1.15%	98.85%
CLIENTSSTAFF	1550	195	157	6	977
Independent variables					
ALBGNI	1550	55.39%	73.70%	1.72%	640.20%
FEMALE	1550	62.61%	24.52%	0.00%	100.00%
DEPOSITS	1550	41.61%	49.31%	0.00%	100.00%
BORROWERRETRATE	1550	74.51%	14.23%	0.06%	100.00%
Control variables					
SIZE (in $m)	1550	77.60	191.29	0.15	2030.00
PAR30	1550	6.08%	9.38%	0.01%	98.52%
LEGAL:					
Bank	65				
Credit Union / Cooperative	87				
NBFI	272				
NGO	269				
Other	15				
Rural Bank	11				

Total	719

Source: own calculation

5.3.2 Multicollinearity test

Table 9 shows the correlation matrix. The pairwise Pearson correlations between the regressors are not in the area of 0.8 to 0.9 and thus no collinearity among two variables can be detected (Kennedy (2008)).

The correlation analysis demonstrates similar correlations between dependent variables and ALBGNI and FEMALE compared to the previous model. The nearly neutral correlation between DEPOSITS and profitability supports the first hypothesis, whereas a positive correlation between BORROWERRETRATE and profitability may indicate that deposit taking MFIs are more profitable than their peers. The negative correlation between DEPOSITS and efficiency is contrary to the second hypothesis and it might imply that deposit taking MFIs are associated with lower operating costs. Lastly, MFIs that offer deposits seem to be associated with higher productivity contrary to the third hypothesis.

Table 9: Adaption of Services Model Correlation Matrix

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1	ROA	1								
2	OPEXPGLP	-0.21	1							
3	CLIENTSSTAFF	-0.01	-0.17	1						
4	ALBGNI	0.01	-0.17	-0.10	1					
5	FEMALE	-0.04	0.20	0.26	-0.39	1				
6	DEPOSITS	-0.03	-0.03	0.48	0.24	-0.01	1			
7	BORROWERRETRATE	0.09	-0.16	0.15	-0.07	0.01	0.05	1		
8	SIZE	0.03	-0.22	0.18	0.18	-0.10	0.25	0.12	1	
9	PAR30	-0.34	-0.06	0.05	-0.01	-0.05	-0.01	-0.04	0.00	1

Source: own calculation

5.3.3 Regression Results

Table 10 presents the results of the FEGLS regressions.

The results of the profitability regression indicate that smaller loans and increased number of female borrowers have no impact on profitability. This finding is similar to the results by Meyer (2019). The deposits taking MFIs seem to have the same profitability compared to the MFIs that attract funding from other sources. The MFIs that retain more borrowers have higher profitability in comparison to their peers. Thus, hypothesis 3.1, which states that a higher borrowers retention rate and presence of savings products have a positive impact on profitability, is partly rejected by the data. Both control variables are significant at 1% significance level indicating that larger MFIs with less risky loan portfolios are more profitable.

The results of the efficiency regression demonstrate that increase in size of loans lead to decrease of OPEXPGLP similar to findings by Meyer (2019). On the contrary, the increase in the number of female borrowers contributes to costs. The absence of savings products and increase in borrowers retention rate lead to decrease in operating costs. Thus, hypothesis 3.2, which assumes that a higher borrowers retention rate and absence of savings products have a positive impact on efficiency, is supported by the data. Both control variables are significant at 1% significance level demonstrating that larger MFIs with less risky loan portfolios can achieve economies of scale and therefore lower their costs.

The productivity regression indicates that a greater number of female clients has a positive impact on productivity. The relationship between DEPOSITS and BORROWERRETRATE and productivity is in line with hypothesis 3.3, which proclaims that a higher borrowers retention rate has a positive impact on productivity, whereas presence of savings products has a neutral impact on productivity. The SIZE control variable is statistically significant showing that larger MFIs are more productive.

Lastly, Multiple R-squared values for all regressions are higher in comparison to the standard model indicating that this model has an additional explanatory power.

Table 10: Adaption of Services Model FEGLS Regression Results

	ROA	OPEXPGLP	CLIENTSSTAF_LN
ALBGNI	0.0071	-0.0267***	0.0265
	(0.0046)	(0.0053)	(0.0231)
FEMALE	0.0320	0.0376*	0.4315***
	(0.0198)	(0.0197)	(0.0956)
DEPOSITS	-0.0024	0.0169***	0.0377
	(0.0053)	(0.0056)	(0.0282)
BORROWERRETRATE	0.0166*	-0.0381***	0.3880***
	(0.0098)	(0.0105)	(0.0462)
SIZE_LN	0.0080***	-0.0342***	0.1029***
	(0.0024)	(0.0027)	(0.0135)
PAR30	-0.3899***	-0.0602*	-0.1241
	(0.0299)	(0.0350)	(0.1511)
Observations	1550	1550	1550
Multiple R-squared	0.774	0.949	0.962

Significance codes: *** 1% level, ** 5% level, * 10% level

Source: own calculation

5.3.4 Robustness Check

Tables 30-32 in Appendix C illustrate the results of endogeneity test. The correlation values between the regressors and error terms are close to zero indicating absence of endogeneity issue. However, it is important to check if the self-selection bias may be a problem for adaption of services model. As discussed by Goedecke, D'Espallier, and Mersland (2016) the MFIs with good SP are more willing to monitor or report their client retention rate. The poor social performers disclose it only if it is above average. However, the comparison of Table 8 and Table 23 in Appendix B indicates that second dimension SP and FP variables have similar values in both samples. Thus, the self-selection bias is not an issue in adaption of services model.

5.4 Benefits to Clients Model

The benefits to clients model includes FP measures as dependent variables and standard measures of SP as well as a number of new borrowers as independent variables. The MFI-specific controls are also added to ensure robustness of the model. The specification of benefits to clients model is the following:

$$ROA_{it}/OPEXGLP_{it}/CLIENTSTAFF\_LN_{it} = \beta_0 + \beta_1 ALBGNI_{it} + \beta_2 FEMALE_{it} + \beta_3 NUMNEWBOR\_LN_{it} + \beta_4 SIZE\_LN_{it} + \beta_5 PAR30_{it} + \beta_{6-10} LEGAL_{it} + v_{it} \quad (17)$$

The detailed description of all variables is provided in Table 21 in Appendix A.

5.4.1 Descriptive Statistics

Table 11 shows different statistical metrics of the data subsample used for the benefits to clients model. The sample represents an unbalanced panel which contains 1’396 year-MFI observations of 706 MFIs from 2008 until 2013. All general variables are similar to the previous model.

The FP variables are almost identical to the previous model.

The average number of new borrowers per year is identical compared to the overall sample in Table 23 in Appendix B.

Table 11: Benefits to Clients Model Descriptive Statistics

Variable	Obs.	Mean	SD	Min	Max
General variables					
YEAR	1396	2011	1	2008	2013

DIAMOND	1396	3.95	0.65	1.00	5.00
REGULATED	1396	62.25%	48.49%	0.00%	100.00%
Dependent variables					
ROA	1396	2.16%	7.32%	-63.54%	45.31%
OPEXPGLP	1396	23.16%	15.14%	1.15%	98.85%
CLIENTSSTAFF	1396	193	159	6	977
Independent variables					
ALBGNI	1396	54.96%	72.79%	1.72%	640.20%
FEMALE	1396	62.62%	24.79%	0.00%	100.00%
NUMNEWBOR (in m)	1396	0.04	0.14	0.00	2.69
Control variables					
SIZE (in $m)	1396	73.46	187.09	0.15	2030.00
PAR30	1396	6.37%	9.86%	0.01%	98.52%
LEGAL:					
Bank	62				
Credit Union / Cooperative	81				
NBFI	270				
NGO	271				
Other	12				
Rural Bank	10				
Total	706				

Source: own calculation

5.4.2 Multicollinearity test

Table 12 shows the correlation matrix. The pairwise Pearson correlations between regressors are not in the area of 0.8 to 0.9 and thus no collinearity among two variables can be detected (Kennedy (2008)).

The correlation analysis demonstrates similar correlations between dependent variables and ALBGNI and FEMALE compared to the previous model. The correlations between main benefits to clients model SP variables and dependent variables are all in line with three hypotheses.

Table 12: Benefits to Clients Model Correlation Matrix

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1	ROA	1							
2	OPEXPGLP	-0.24	1						
3	CLIENTSSTAFF	-0.04	-0.16	1					
4	ALBGNI	0.03	-0.15	-0.10	1				
5	FEMALE	-0.05	0.18	0.28	-0.41	1			
6	NUMNEWBOR	0.00	-0.12	0.25	-0.10	0.23	1		
7	SIZE	0.04	-0.22	0.19	0.17	-0.09	0.39	1	

8	PAR30	-0.36	-0.05	0.07	-0.01	-0.05	0.11	0.00	1

Source: own calculation

5.4.3 Regression Results

Table 13 presents the results of the FEGLS regressions.

The results of the profitability regression fully support hypothesis 4.1, which states that a greater number of new borrowers has a neutral impact on profitability. Both control variables are significant at 1% significance level indicating that larger MFIs with less risky loan portfolios are more profitable.

The results of the efficiency regression fully support hypothesis 4.2, which proclaims that a greater number of new borrowers has a negative impact on efficiency. Only SIZE control variable is statistically significant meaning that larger MFIs can achieve economies of scale and therefore lower their costs.

The results of the productivity regression fully support hypothesis 4.3, which predicts that a greater number of new borrowers has a positive impact on productivity. The SIZE control variable is statistically significant showing that larger MFIs are more productive.

Lastly, Multiple R-squared values for all regressions are higher in comparison to the standard model indicating that this model has an additional explanatory power.

Table 13: Benefits to Clients Model FEGLS Regression Results

	ROA	OPEXPGLP	CLIENTSSTAF_LN
ALBGNI	-0.0035	-0.0033	-0.0715***
	(0.0051)	(0.0053)	(0.0249)
FEMALE	0.0253	0.0409*	0.3896***
	(0.0226)	(0.0228)	(0.1078)
NUMNEWBOR_LN	0.0010	0.0045**	0.0578***
	(0.0020)	(0.0020)	(0.0096)
SIZE_LN	0.0147***	-0.0459***	0.1160***
	(0.0030)	(0.0032)	(0.0164)
PAR30	-0.3799***	-0.0168	-0.1156
	(0.0316)	(0.0343)	(0.1595)
Observations	1396	1396	1396
Multiple R-squared	0.797	0.953	0.966
Significance codes: *** 1% level, ** 5% level, * 10% level			

Source: own calculation

5.4.4 Robustness Check

Tables 33-35 in Appendix C illustrate the results of endogeneity test. The correlation values between the regressors and error terms are close to zero indicating absence of endogeneity issue. The comparison of Table 11 and Table 23 in Appendix B indicates that SP and FP variables have similar values in both samples. Thus, the self-selection bias is not an issue in benefits to clients model.

5.5 Social Responsibility Model

The SR model includes FP measures as dependent variables and standard measures of SP as well as a staff turnover ratio as independent variables. The MFI-specific controls are also added to ensure robustness of the model. The specification of SR model is the following:

$$ROA_{it}/OPEXGLP_{it}/CLIENTSTAFF\_LN_{it} = \beta_0 + \beta_1 ALBGNI_{it} + \beta_2 FEMALE_{it} + \beta_3 STAFFTURN_{it} + \beta_4 SIZE\_LN_{it} + \beta_5 PAR30_{it} + \beta_{6-10} LEGAL_{it} + v_{it} \tag{18}$$

The detailed description of all variables is provided in Table 21 in Appendix A.

5.5.1 Descriptive Statistics

Table 14 shows different statistical metrics of the data subsample used for the SR model. The subsample represents an unbalanced panel which contains 1’977 year-MFI observations of 807 MFIs from 2009 until 2014. The sample is significantly larger compared to the previous model. All general variables are similar to the previous model.

The average MFI from this subsample is significantly more productive than its peers in the previous model.

The average staff turnover per year is similar to the value in overall sample in Table 23 in Appendix B.

Table 14: Social Responsibility Model Descriptive Statistics

Variable	Obs.	Mean	SD	Min	Max
General variables					
YEAR	1977	2012	1	2009	2014
DIAMOND	1977	3.96	0.70	1.00	5.00
REGULATED	1977	62.27%	48.48%	0.00%	100.00%
Dependent variables					
ROA	1977	2.20%	6.93%	-63.54%	38.18%
OPEXPGLP	1977	23.68%	16.38%	1.15%	99.74%
CLIENTSSTAFF	1977	214	172	5	982

Independent variables					
ALBGNI	1977	52.97%	71.29%	1.61%	674.78%
FEMALE	1977	63.99%	24.94%	0.00%	100.00%
STAFFTURN	1977	21.74%	17.17%	0.31%	99.77%
Control variables					
SIZE (in $m)	1977	79.86	209.45	0.08	2930.00
PAR30	1977	6.13%	9.48%	0.01%	98.52%
LEGAL:					
Bank	74				
Credit Union / Cooperative	96				
NBFI	319				
NGO	280				
Other	14				
Rural Bank	24				
Total	807				

Source: own calculation

5.5.2 Multicollinearity test

Table 15 shows the correlation matrix. The pairwise Pearson correlations between regressors are not in the area of 0.8 to 0.9 and thus no collinearity among two variables can be detected (Kennedy (2008)).

The correlation analysis demonstrates similar correlations between dependent variables and ALBGNI and FEMALE compared to the previous model. The correlations between the main SR model SP variables and dependent variables are all in line with three hypotheses.

Table 15: Social Responsibility Model Correlation Matrix

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1	ROA	1							
2	OPEXPGLP	-0.23	1						
3	CLIENTSSTAFF	-0.01	-0.21	1					
4	ALBGNI	0.00	-0.20	-0.11	1				
5	FEMALE	-0.01	0.21	0.21	-0.42	1			
6	STAFFTURN	-0.04	0.16	-0.15	-0.11	0.14	1		
7	SIZE	0.04	-0.20	0.20	0.18	-0.13	-0.04	1	
8	PAR30	-0.29	-0.03	0.04	-0.01	-0.07	0.07	0.00	1

Source: own calculation

5.5.3 Regression Results

Table 16 presents the results of the FEGLS regressions.

The results of the profitability regression fully support hypothesis 5.1, which proclaims that a lower staff turnover ratio has a positive impact on profitability. Both control variables are significant at 1% significance level indicating that larger MFIs with less risky loan portfolios are more profitable.

The results of the efficiency regression show that a decreased dropout rate does not lead to decreased operating costs. This result can be explained by the fact that additional costs related to training are offset if new recruits get lower salaries. Therefore, hypothesis 5.2, which states that a lower staff turnover ratio has a positive impact on efficiency, is not supported by the data. Both control variables are significant at 1% significance level demonstrating that larger MFIs with less risky loan portfolios can achieve economies of scale and therefore lower their costs.

The results of the productivity regression fully support hypothesis 5.3, which assumes that a lower staff turnover ratio has a positive impact on productivity. The SIZE control variable is statistically significant showing that larger MFIs are more productive.

Lastly, Multiple R-squared values for all regressions are higher in comparison to the standard model indicating that this model has an additional explanatory power.

Table 16: Social Responsibility Model FEGLS Regression Results

	ROA	OPEXPGLP	CLIENTSSTAF_LN
ALBGNI	0.0019	-0.0172***	-0.1526***
	(0.0028)	(0.0033)	(0.0180)
FEMALE	0.0158	0.0189	0.2414***
	(0.0147)	(0.0134)	(0.0809)
STAFFTURN	-0.0282***	0.0093	-0.2113***
	(0.0069)	(0.0076)	(0.0402)
SIZE_LN	0.0058***	-0.0351***	0.1075***
	(0.0019)	(0.0023)	(0.0122)
PAR30	-0.3022***	-0.1383***	-0.1496
	(0.0231)	(0.0258)	(0.1213)
Observations	1977	1977	1977
Multiple R-squared	0.794	0.947	0.955
Significance codes: *** 1% level, ** 5% level, * 10% level			

Source: own calculation

5.5.4 Robustness Check

Tables 36-38 in Appendix C illustrate the results of endogeneity test. The correlations values between the regressors and error terms are close to zero indicating absence of endogeneity issue. The comparison of Table 14 and Table 23 in Appendix B indicates that SP and FP variables have similar values in both samples. Thus, the self-selection bias is not an issue in the SR model.

5.6 Comparison of the Social Performance Models

This section gives a summary of the empirical results presented in the previous chapters and summarises the findings. This thesis chooses not to estimate a full model with all SP variables because it would lead to a loss of too many observations and potential multicollinearity issues. Furthermore, it presents the results of hypotheses tests. Lastly, the endogeneity issue is discussed.

5.6.1 Profitability

Table 17 demonstrates the results of the profitability regressions. The overall relationship between the average loan size and profitability is neutral. This finding is similar to the previous research (e.g. Meyer (2019)). The higher percentage of female borrowers seems to have overall neutral effect on profitability. This result is supported by the previous literature (e.g. Bassem (2012)). The greater offices network coverage has a small negative impact on profitability. This outcome supports the assumption that additional offices generate insufficient revenue to cover additional operational costs. The larger number of rural borrowers has a neutral effect on profitability. This result confirms the expectation that higher operating costs and lower repayment risks associated with rural clients offset each other. The deposits taking MFIs seem to have the same profitability as MFIs that do not offer deposits. The higher percentage of retained borrowers has a small positive effect on profitability. This outcome indicates that returning borrowers may be associated with less operating costs because their service requires less effort from MFI’s staff. The increasing number of new borrowers has a neutral link to profitability. This finding supports the hypothesis that revenues and costs caused by additional borrowers offset each other. The lower staff turnover ratio has a small positive impact on profitability. This result reinforces the assumption that the additional operating costs related to the training of new recruits have a negative effect on profitability. Both control variables are significant at 1% significance level across all models. This outcome indicates that larger MFIs with less risky loan portfolios are more profitable.

Multiple R-squared values for all alternative models are higher in comparison to the standard model indicating that these models have an additional explanatory power.

Table 17: Summary of Profitability Regressions

Model	Standard	Targeting and Outreach	Adaption of Services	Benefits to Clients	Social Responsibility
Variable	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) ROA
ALBGNI	0.0096***	-0.0137***	0.0071	-0.0035	0.0019
	(0.0006)	(0.0030)	(0.0046)	(0.0051)	(0.0028)
FEMALE	0.0253***	0.0320***	0.0320	0.0253	0.0158
	(0.0054)	(0.0105)	(0.0198)	(0.0226)	(0.0147)
OFFICES_LN		-0.0121***			
		(0.0017)			
RURAL		0.0048			
		(0.0047)			
DEPOSITS			-0.0024		
			(0.0053)		
BORROWERRETRATE			0.0166*		
			(0.0098)		
NUMNEWBOR_LN				0.0010	
				(0.0020)	
STAFFTURN					-0.0282***
					(0.0069)
SIZE_LN	0.0150***	0.0223***	0.0080***	0.0147***	0.0058***
	(0.0005)	(0.0015)	(0.0024)	(0.0030)	(0.0019)
PAR30	-0.2269***	-0.2838***	-0.3899***	-0.3799***	-0.3022***
	(0.0079)	(0.0112)	(0.0299)	(0.0316)	(0.0231)
Observations	7298	2845	1550	1396	1977
Multiple R-squared	0.634	0.735	0.774	0.797	0.794
Significance codes: *** 1% level, ** 5% level, * 10% level					

Source: own calculation

5.6.2 Efficiency

Table 18 illustrates the results of the efficiency regressions. The results for the average loan size show that larger loans lead to a small increase in efficiency of MFIs. This finding is in line with the previous studies (e.g. Hermes, Lensink, and Meesters (2011) and Meyer (2019)). The higher percentage of female borrowers decreases efficiency of MFIs. This result is supported by the previous literature (e.g. D'espallier, Guerin, and Mersland (2013) and Meyer (2019)). The greater offices network coverage has a negative effect on efficiency. This outcome confirms the assumption that additional offices generate additional operational costs. The larger number of rural borrowers has a small positive impact on efficiency. This result rejects the expectation that rural clients are less educated than urban customers and thus might be not able to use mobile banking services. The deposits taking MFIs seem to experience higher operating costs than MFIs that do not mobilise deposits. One possible explanation of this outcome could be the fact that staff members of MFIs must spend additional effort and time to attract deposits. The higher percentage of retained borrowers has a small positive impact on efficiency. This outcome indicates that the returning borrowers are already familiar with mechanics of lending process and thus require less assistance from staff members. Thus, the operating costs decrease. The increasing number of new borrowers has a negative effect on efficiency. This finding supports the hypothesis that new clients require more time and assistance from staff members and thus cause increased operational expenses. The lower staff turnover ratio seems to have no effect on efficiency. This result reinforces the assertion that many firms give new employees - all else being equal - lower wages in comparison to the existing staff. Thus, this difference seems to cover all operating expenses related to training of new recruits. The size of MFIs has a negative impact on operating costs meaning that larger MFIs can achieve economies of scale and therefore lower their operating costs. The MFIs with less risky loan portfolios can benefit from lower operating costs.

Multiple R-squared values for all alternative models are higher in comparison to the standard model indicating that these models have an additional explanatory power.

Table 18: Summary of Efficiency Regressions

Model	Standard	Targeting and Outreach	Adaption of Services	Benefits to Clients	Social Responsibility
Variable	(1) OPEXPGLP	(2) OPEXPGLP	(3) OPEXPGLP	(4) OPEXPGLP	(5) OPEXPGLP
ALBGNI	-0.0105***	-0.0034	-0.0267***	-0.0033	-0.0172***
	(0.0008)	(0.0043)	(0.0053)	(0.0053)	(0.0033)
FEMALE	0.0246*	0.0196	0.0376*	0.0409*	0.0189
	(0.0060)	(0.0140)	(0.0197)	(0.0228)	(0.0134)
OFFICES_LN		0.0271***			
		(0.0028)			
RURAL		-0.0238***			
		(0.0065)			
DEPOSITS			0.0169***		
			(0.0056)		
BORROWERRETRATE			-0.0381***		
			(0.0105)		
NUMNEWBOR_LN				0.0045**	
				(0.0020)	
STAFFTURN					0.0093

					(0.0076)
SIZE_LN	-0.0395***	-0.0560***	-0.0342***	-0.0459***	-0.0351***
	(0.0007)	(0.0022)	(0.0027)	(0.0032)	(0.0023)
PAR30	0.0250***	-0.0427***	-0.0602*	-0.0168	-0.1383***
	(0.0091)	(0.0157)	(0.0350)	(0.0343)	(0.0258)
Observations	7298	2845	1550	1396	1977
Multiple R-squared	0.854	0.923	0.949	0.953	0.947
Significance codes: *** 1% level, ** 5% level, * 10% level					

Source: own calculation

5.6.3 Productivity

Table 19 shows the results of the productivity regressions. The results for the average loan size indicate that larger loans lead to decrease in productivity of MFIs. Smaller loans are delivered faster than larger loans because most MFIs offer small loans through the group lending methodology, whereas large loans are normally delivered through individual lending. The group lending is safer than individual lending, since group members act as guarantors for each other and thus time and effort for credit analysis of borrowers in the group is lower compared to individual lending. This finding is in line with the previous research (Gonzalez (2010)). The higher percentage of female borrowers increases productivity of MFIs. This result can be explained by the theoretical arguments from the previous literature. Armendáriz and Morduch (2005) emphasize that women are poorer than men. Thus, they request smaller loans. Since smaller loans are delivered faster than larger loans, MFIs with a higher number of female borrowers seem to be more productive than their peers. The greater offices network coverage has a small negative impact on productivity. One possible explanation for this outcome could be an assumption that new offices attract very few clients during the first years after the opening and thus lower the overall number of clients per staff member. The larger number of rural borrowers has no statistically significant effect on productivity. This result rejects the expectation that service of rural clients requires more time of staff members than the service of urban customers and thus reduces productivity. The deposits taking MFIs seem to be as productive as MFIs that do not mobilise deposits. The higher percentage of retained borrowers increases productivity. This outcome indicates that staff members spend less time on the borrowers who are already familiar with lending processes and thus can serve more clients. The increasing number of new borrowers has a small positive effect on productivity. This finding supports the hypothesis that MFIs respond to increasing number of clients by improving their productivity. The lower staff turnover ratio seems to increase productivity of MFIs. This result reinforces the assertion that new employees are less productive than current ones. This finding is consistent with the previous research by Gonzalez (2010). The size of MFIs has a positive impact on productivity meaning that larger MFIs are more productive because they have better infrastructure to serve clients. The larger portion of loans greater than 30 days past due has a neutral link to productivity.

Multiple R-squared values for all alternative models are higher in comparison to the standard model indicating that these models have an additional explanatory power.

Table 19: Summary of Productivity Regressions

Model	Standard	Targeting and Outreach	Adaption of Services	Benefits to Clients	Social Responsibility
Variable			CLIENTSSTAF_LN		
ALBGNI	-0.3528***	-0.2884***	0.0265	-0.0715***	-0.1526***
	(0.0072)	(0.0214)	(0.0231)	(0.0249)	(0.0180)
FEMALE	0.1201***	0.2001***	0.4315***	0.3896***	0.2414***
	(0.0280)	(0.0671)	(0.0956)	(0.1078)	(0.0809)
OFFICES_LN		-0.0911***			
		(0.0148)			
RURAL		0.0183			
		(0.0336)			
DEPOSITS			0.0377		
			(0.0282)		
BORROWERRETRATE			0.3880***		
			(0.0462)		
NUMNEWBOR_LN				0.0578***	
				(0.0096)	
STAFFTURN					-0.2113***
					(0.0402)
SIZE_LN	0.0606***	0.1713***	0.1029***	0.1160***	0.1075***
	(0.0038)	(0.0123)	(0.0135)	(0.0164)	(0.0122)
PAR30	0.0137***	0.0052	-0.1241	-0.1156	-0.1496
	(0.0467)	(0.0752)	(0.1511)	(0.1595)	(0.1213)
Observations	7298	2845	1550	1396	1977
Multiple R-squared	0.869	0.942	0.962	0.966	0.955
Significance codes: *** 1% level, ** 5% level, * 10% level					

Source: own calculation

5.6.4 Hypotheses Test

Table 20 shows a summary of the relationships between the predicted and actual effect of the explanatory variables on the dependent variables. The plus sign means a positive impact, the minus sign means a negative effect, and zero indicates no significant effect.

Table 20: Hypotheses test

Variables	ROA		OPEXGLP		CLIENTSSTAF_LN	
	Expected	Actual	Expected	Actual	Expected	Actual
ALBGNI	0	0	-	-	-	-
FEMALE	0	0	+	+	+	+
OFFICES_LN	0	-	+	+	+	-
RURAL	0	0	+	-	+	0
DEPOSITS	+	0	+	+	0	0
BORROWERRETRATE	+	+	-	-	+	+
NUMNEWBOR_LN	0	+	+	+	+	+
STAFFTURN	-	-	+	0	-	-

Source: own research

5.6.5 Endogeneity Test

Tables 24-38 in Appendix C illustrate the results of endogeneity test. The correlation values between the regressors and error terms are close to zero indicating absence of the endogeneity issue caused by high correlation between the error terms and regressors. Consequently, the omitted- variable bias should not be an issue in all models.

The comparison of Tables 2,5,8,11, and 14 with Table 23 from Appendix B indicates that third dimension SP and FP variables have similar values. Thus, the self-selection bias is not a problem in all models.

The last possible source of endogeneity is reverse causality. This problem arises when dependent variable causes changes in explanatory variables (Baltagi (2005)). Since MFIs with solid FP might choose to improve their SP, the possibility of reverse causality cannot be completely dismissed. However, this assumption is very unlikely to be true because MFIs cannot achieve a certain level of FP without first defining the SP level they want to reach.

6 Conclusion

This thesis investigates the relationship between outreach and financial return of MFIs. Most existing studies on the topic use an average loan size and a percentage of female borrowers as standard proxies for depth of outreach. However, many researchers argue that depth of outreach is just one of many dimensions that describe social mission of MFIs. Thus, some academics are developing alternative measures of outreach to refine the definitions and reporting metrics of outreach.

The objective of this study consists of two steps. First, it examines the topic using the average loan size and the percentage of female borrowers and compares the results to the previous literature. Second, it develops various alternative proxies for outreach and adds them to standard proxies for depth of outreach. The alternative metrics of social outreach must provide more in-depth analysis of various aspects of social fieldwork performed by MFIs and help to improve the existing measures of social outreach. Furthermore, this thesis critically reflects on the additional value of more detailed outreach metrics and the potential explanatory power of adding such variables to the standard models used in current literature.

The objective of this thesis is achieved by examining a dataset provided by UZH DBF's Center for Sustainable Finance and Private Wealth. The full dataset includes 16'918 year-MFI observations from 1995 to 2014. This dataset represents the aggregation of "diamond" and "legal" history datasets with other purchased datasets. The original data were obtained from the MIX. Furthermore, this thesis constructs additional SP metrics from the original MIX data and expands the dataset.

The results of the study indicate that smaller loans and higher percentage of women borrowers have an overall neutral effect on profitability - which is similar to findings by Bassem (2012) and Meyer (2019). The larger loans have a positive effect on efficiency of MFIs, whereas higher percentage of women borrowers decrease efficiency. Both findings are supported by the previous studies (e.g. Hermes, Lensink, and Meesters (2011), D'espallier, Guerin, and Mersland (2013), and Meyer (2019)). The findings also indicate that smaller loans and higher percentage of female borrowers increase productivity of MFIs. Both results are in line with the previous literature (e.g. Gonzalez (2010)). Thus, the empirical analysis confirms the previous findings on the relationship between outreach measured by standard proxies and financial return.

The findings with respect to the effect of alternative proxies for outreach on profitability show that the greater offices network coverage has a small negative impact on profitability. This outcome supports the assumption that additional offices generate insufficient revenue to cover additional operational costs. The higher percentage of retained borrowers has a small positive effect on profitability. This outcome indicates that returning borrowers may be associated with lower operating costs because their service requires less effort from MFI's staff. The lower staff turnover ratio has a small positive impact on profitability. This result reinforces the assumption that the additional operating costs related to the training of new recruits have a negative effect on profitability. In conclusion, it seems that higher outreach has a slightly positive impact on profitability.

The findings with respect to the effect of alternative proxies for outreach on efficiency indicate that the greater offices network coverage has a negative effect on efficiency. This outcome confirms the assumption that additional offices generate additional operational costs. The larger number of rural borrowers has a small positive impact on efficiency. This result subverts the expectation that rural clients are less educated than urban customers and thus might be not able to use mobile banking services. The deposits taking MFIs seem to experience higher operating costs than MFIs that do not mobilise deposits. One possible explanation of this outcome could be the fact that staff members of MFIs must spend additional effort and time to attract deposits. The higher percentage of retained borrowers has a small positive impact on efficiency. This outcome indicates that the returning borrowers are already familiar with mechanics of lending process and thus require less assistance from staff members which results in lower costs. The increasing number of new borrowers has a negative effect on efficiency. This finding supports the assumption that new clients require more time and assistance from staff members and thus cause increased operational expenses. In conclusion, it seems that better SP has a neutral impact on efficiency.

The findings with respect to the effect of alternative proxies for outreach on productivity reveal that the greater offices network coverage has a small negative impact on productivity. One possible explanation for this outcome could be an assumption that new offices attract very few clients during the first years after the opening and thus lower the overall number of clients per staff member. The higher percentage of retained borrowers increases productivity. This outcome indicates that staff members spend less time on the borrowers who are already familiar with lending processes and thus can serve more clients. The increasing number of new borrowers has a small positive effect on productivity. This finding supports the hypothesis that MFIs respond to increasing number of clients by improving their productivity.

The lower staff turnover ratio seems to increase productivity of MFIs. This result reinforces the assertion that new employees are less productive than current ones and is consistent with the previous research by Gonzalez (2010). In conclusion, it seems that higher outreach has a slightly positive impact on productivity.

All models with alternative proxies for outreach exhibit higher explanatory power in terms of R-squared compared to the model with only standard proxies.

The findings of this thesis have a number of limitations which must be considered when interpreting the results. First, the empirical analysis is based on the sample that includes only limited number of MFIs. Although this sample is large, it does not represent the entire microfinance universe. Thus, statistical inferences drawn from the study sample cannot be applied to all existing MFIs.

Second, the sample used in this thesis is plagued by the overwriting problem. Since this sample is an aggregation of data from various datasets, it contains multiple observations that either changed over time or were misleading. Thus, these observations were overwritten, and as a result, some results from empirical models may not apply to the entire time range of the sample.

Third, the results of the study may suffer from reverse causality. It is still not clear whether MFIs choose to improve their outreach when they reach financial sustainability, or if they reach financial sustainability by improving their social outreach. Thus, future research can investigate this question using more sophisticated empirical models that will allow to completely exclude reverse causality.

Lastly, many outreach variables are not available due to insufficient number of observations. Unfortunately, the sample used in this study contains very few observations of social metrics that are best suited to analyse the impact of outreach on financial return. Thus, the missing variables are substituted with SP measures that describe similar aspects of outreach. However, the substitutes may not always measure the same effect compared to original metrics. Furthermore, most SP indicators lack additional information for in-depth analysis. For example, the existing survey only tracks borrowers retention rate and does not distinguish between poverty level of retained borrowers. Thus, it is not possible to analyse whether MFIs are able to retain the poorest clients. It is worth emphasizing that outreach metrics are the tools that help to answer the ultimate question: Do MFIs give poor populations an opportunity become self-sufficient? This question cannot be answered with the existing data on microfinance. Therefore, a possible policy implication would be to incentivise various organizations that develop social metrics and platforms that collect microfinance data to closely work with academia. This is the only way to ensure collection of data that can be practical for future research.

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A Appendix

Table 21: Description of Variables

Name of variable	**Description**
Dependent variables	
ROA	Net operating income (less of taxes) compared to average assets. This ratio is net of income taxes and excludes donations and non-operating items.
OPEXPGLP	Total operating expense compared to average GLP. Measures all costs incurred to deliver loans (personnel and administrative expenses as well as non-cash expenses such depreciation and amortization).
CLIENTSSTAFF	Total number of clients divided by total personnel. Aids to assess the overall productivity of the financial institution's employees in terms of serving borrowers.
Independent variables	
ALBGNI	Average outstanding loan balance compared to local GNI per capita. The indicator measured with GNI per capita that is calculated in national currency is usually converted to U.S. dollars at official exchange rates for comparisons across economies, although an alternative rate is used when the official exchange rate is judged to diverge by an exceptionally large margin from the rate actually applied in international transactions.
FEMALE	Number of active female borrowers as a percentage of total borrowers at period end.
OFFICES	The number of staffed points of service and administrative sites / branches used to deliver or support the delivery of financial services and wide array of face-to-face and automated services to

	clients.
RURAL	Number of rural clients as a percentage of total clients at period end.
DEPOSITS	Dummy variable indicating whether MFI takes deposits.
BORROWERRETRATE	Percentage of retained borrowers as calculated by active borrowers at the end of the period divided by active borrowers at the beginning of the period and new borrowers during the period
NUMNEWBOR	Number of new borrowers attracted by MFI during the period.
STAFFTURN	Percentage of staff (permanent and contract) having left the financial institution during the last reporting year, as calculated by the number of staff exiting the organization during the period divided by the average number of permanent and contract staff.
Control variables	
SIZE	Size variable is measured by total assets which is total value of resources controlled by the MFIs as a result of past events and from which future economic benefits are expected to flow to the MFIs. For calculation purposes, assets are the sum of each individual asset accounts listed.
PAR30	Represents the portion of loans greater than 30 days past due, including the value of all renegotiated loans (restructured, rescheduled, refinanced and any other revised loans) compared to GLP.
LEGAL	Current legal status of MFI. This variable contains 6 categories: Bank, Credit Union / Cooperative, NBFI, NGO, Rural Bank, Other.

Source: MIX (2018)

B Appendix

Data preparation process

This section briefly describes the process of data preparation for each SP model in the empirical analysis section of the thesis.

MIX Dataset

Table 22 demonstrates the initial MIX dataset which was provided by UZH DBF's Center for Sustainable Finance and Private Wealth. All MFI-year observations with year equal to zero are removed from the dataset.

Table 22: MIX Dataset

Variable	Obs.	Mean	SD	Min	Max
General variables					
YEAR	16918	2008	4	1995	2014
DIAMOND	14626	3	1.17	0.00	5.00
REGULATED	14090	65.03%	47.69%	0.00%	100.00%
Dependent variables					
ROA	11046	0.17%	17.51%	-746.37%	100.89%
OPEXPGLP	11048	30.69%	60.80%	-133.29%	2652.19%
CLIENTSSTAFF	16918	163	294	0	13709
Independent variables					
ALBGNI	13014	84.54%	558.51%	0.00%	55772.83%
FEMALE	10942	64.73%	27.81%	0.00%	668.91%
OFFICES	9171	45	184	0	5000
RURAL	4375	54.85%	33.87%	0.00%	100.00%
DEPOSITS	16918	35.05%	47.71%	0.00%	100.00%
BORROWERRETRATE	2343	75.67%	25.30%	0.00%	728.99%
NUMNEWBOR (in m)	2289	1.38	45.59	0.00	1542.81
STAFFTURN	2774	21.70%	22.59%	0.00%	297.17%
Control variables					
SIZE (in $m)	13680	47.99	220.58	0.00	6130.00
PAR30	11329	7.03%	15.78%	0.00%	711.43%
LEGAL:					
Bank	160				
Credit Union / Cooperative	423				
NBFI	531				
NGO	732				
Other	16				
Rural Bank	135				
Total	1997				

Source: own calculation

Overall Sample

The overall sample is created by modifying MIX dataset from the initial dataset. The following criteria are applied for data cleaning process:

1) All MFI-year observations with missing general (i.e. name, year, diamond, and regulation status) and dependent (i.e. ROA, OPEXGLP, CLIENTSTAFF) variables are removed from the dataset.

2) All MFI-year observations with diamonds rating and year equal to zero are removed from the dataset.

3) All MFI-year observations with missing regulation information are assumed to be non-regulated.

4) All MFI-year observations with a negative ROA exceeding 100% are removed from the dataset.

5) All MFI-year observations with the OPEXGLP less than 1% and larger than 100% are removed from the dataset.

6) All MFI-year observations with the CLIENTSTAFF less than two and larger than 999 are removed from the dataset.

7) All MFI-year observations with the ALBGNI less than 1% and larger than 1000% are removed from the dataset.

8) All MFI-year observations with the SIZE equal to zero are removed from the dataset.

9) All MFI-year observations with the PAR30 less or equal to 0% and larger than 100% are removed from the dataset.

10) All MFI-year observations with zero offices are removed from the dataset.

11) All MFI-year observations with missing values for deposits are assumed to have no deposits.

12) All MFI-year observations with the BORROWERRETRATE less or equal to 0% and larger than 100% are removed from the dataset.

13) All MFI-year observations with the STAFFTURN less or equal to 0% and larger than 100% are removed from the dataset.

Table 23 illustrates the dataset resulting from data cleaning process. This dataset is used as basis for preparation of all subsamples for all SP regressions.

Table 23: Overall Sample Descriptive Statistics

Variable	Obs.	Mean	SD	Min	Max
General variables					
YEAR	8077	2008	3	1997	2014
DIAMOND	8077	4	0.79	1.00	5.00
REGULATED	8077	63.84%	48.05%	0.00%	100.00%
Dependent variables					
ROA	8077	1.87%	8.46%	-95.63%	100.89%
OPEXPGLP	8077	25.31%	18.03%	1.00%	99.74%
CLIENTSSTAFF	8077	219	175	3	999
Independent variables					
ALBGNI	8076	62.48%	89.88%	1.08%	990.09%
FEMALE	7299	63.93%	25.79%	0.00%	100.00%
OFFICES	6681	48	189	1	3334
RURAL	2903	53.97%	32.44%	0.00%	100.00%
DEPOSITS	8077	45.20%	49.77%	0.00%	100.00%
BORROWERRETRATE	1568	74.56%	14.23%	0.06%	100.00%
NUMNEWBOR (in m)	1396	0.04	0.14	0.00	2.69
STAFFTURN	1977	21.65%	17.19%	0.31%	99.77%
Control variables					
SIZE (in $m)	8077	53.66	195.99	0.00	5600.00
PAR30	8077	6.62%	9.34%	0.01%	99.20%
LEGAL:					
Bank	127				
Credit Union / Cooperative	317				
NBFI	494				
NGO	512				
Other	20				
Rural Bank	109				
Total	1579				

Source: own calculation

Social Performance Subsamples

The subsamples for SP regressions were created from the overall sample by selecting independent variables for respective SP models and removing all MFI-year observations that contain missing SP indicators.

C Appendix

Table 24: Standard Model Profitability Endogeneity Test

		1	*2*	*3*	*4*	*5*
1	ALBGNI	1				
2	FEMALE	-0.38	1			
3	SIZE_LN	0.12	-0.13	1		
4	PAR30	0.03	-0.10	-0.09	1	
5	ERROR TERMS	-0.01	0.02	0.01	-0.02	1

Source: own calculation

Table 25: Standard Model Efficiency Endogeneity Test

		1	*2*	*3*	*4*	*5*
1	ALBGNI	1				
2	FEMALE	-0.38	1			
3	SIZE_LN	0.12	-0.13	1		
4	PAR30	0.03	-0.10	-0.09	1	
5	ERROR TERMS	0.01	0.00	-0.03	0.02	1

Source: own calculation

Table 26: Standard Model Productivity Endogeneity Test

		1	*2*	*3*	*4*	*5*
1	ALBGNI	1				
2	FEMALE	-0.38	1			
3	SIZE_LN	0.12	-0.13	1		
4	PAR30	0.03	-0.10	-0.09	1	
5	ERROR TERMS	-0.01	0.01	0.01	0.00	1

Source: own calculation

Table 27: Targeting and Outreach Model Profitability Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*	*7*
1	ALBGNI	1						
2	FEMALE	-0.41	1					
3	OFFICES_LN	-0.07	0.24	1				
4	RURAL	-0.11	0.13	0.12	1			
5	SIZE_LN	0.19	-0.12	0.73	-0.05	1		
6	PAR30	0.02	-0.09	0.01	0.00	-0.05	1	
7	ERROR TERMS	0.00	0.02	0.01	-0.02	0.03	-0.02	1

Source: own calculation

Table 28: Targeting and Outreach Model Efficiency Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*	*7*
1	ALBGNI	1						
2	FEMALE	-0.41	1					
3	OFFICES_LN	-0.07	0.24	1				
4	RURAL	-0.11	0.13	0.12	1			
5	SIZE_LN	0.19	-0.12	0.73	-0.05	1		
6	PAR30	0.02	-0.09	0.01	0.00	-0.05	1	
7	ERROR TERMS	0.01	-0.03	-0.03	-0.01	-0.01	0.04	1

Source: own calculation

Table 29: Targeting and Outreach Model Productivity Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*	*7*
1	ALBGNI	1						
2	FEMALE	-0.40	1					
3	OFFICES_LN	-0.05	0.15	1				
4	RURAL	-0.09	0.13	0.12	1			
5	SIZE_LN	0.15	-0.09	0.35	-0.04	1		
6	PAR30	0.01	-0.06	0.06	0.01	-0.02	1	
7	ERROR TERMS	0.00	0.00	0.03	-0.01	0.03	0.02	1

Source: own calculation

Table 30: Adaption of Services Model Profitability Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*	*7*
1	ALBGNI	1						
2	FEMALE	-0.39	1					
3	DEPOSITS	0.24	-0.01	1				
4	BORROWERRETRATE	-0.07	0.01	0.05	1			
5	SIZE_LN	0.23	-0.14	0.24	0.18	1		
6	PAR30	-0.01	-0.05	-0.01	-0.04	-0.03	1	
7	ERROR TERMS	-0.01	0.01	0.01	0.00	-0.02	-0.04	1

Source: own calculation

Table 31: Adaption of Services Model Efficiency Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*	*7*
1	ALBGNI	1						
2	FEMALE	-0.39	1					
3	DEPOSITS	0.24	-0.01	1				
4	BORROWERRETRATE	-0.07	0.01	0.05	1			
5	SIZE_LN	0.23	-0.14	0.24	0.18	1		
6	PAR30	-0.01	-0.05	-0.01	-0.04	-0.03	1	
7	ERROR TERMS	0.01	-0.04	0.00	-0.02	0.00	0.03	1

Source: own calculation

Table 32: Adaption of Services Model Productivity Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*	*7*
1	ALBGNI	1						
2	FEMALE	-0.39	1					
3	DEPOSITS	0.02	0.04	1				
4	BORROWERRETRATE	-0.06	0.07	0.07	1			
5	SIZE_LN	0.19	-0.08	0.01	0.13	1		
6	PAR30	0.00	-0.01	-0.03	-0.04	-0.02	1	
7	ERROR TERMS	0.01	0.00	0.00	-0.02	0.03	-0.04	1

Source: own calculation

Table 33: Benefits to Clients Model Profitability Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*
1	ALBGNI	1					
2	FEMALE	-0.41	1				
3	NUMNEWBOR	-0.11	0.32	1			
4	SIZE_LN	0.23	-0.13	0.71	1		
5	PAR30	-0.01	-0.05	-0.07	-0.02	1	
6	ERROR TERMS	0.03	0.00	-0.02	-0.02	-0.01	1

Source: own calculation

Table 34: Benefits to Clients Model Efficiency Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*
1	ALBGNI	1					
2	FEMALE	-0.41	1				
3	NUMNEWBOR	-0.11	0.32	1			
4	SIZE_LN	0.23	-0.13	0.71	1		
5	PAR30	-0.01	-0.05	-0.07	-0.02	1	
6	ERROR TERMS	0.01	0.00	0.03	0.02	-0.01	1

Source: own calculation

Table 35: Benefits to Clients Model Productivity Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*
1	ALBGNI	1					
2	FEMALE	-0.41	1				
3	NUMNEWBOR	-0.11	0.32	1			
4	SIZE_LN	0.23	-0.13	0.71	1		
5	PAR30	-0.01	-0.05	-0.07	-0.02	1	
6	ERROR TERMS	0.06	-0.04	0.01	0.03	0.02	1

Source: own calculation

Table 36: Social Responsibility Model Profitability Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*
1	ALBGNI	1					
2	FEMALE	-0.42	1				
3	NUMNEWBOR	-0.11	0.14	1			
4	SIZE_LN	0.24	-0.19	0.00	1		
5	PAR30	-0.01	-0.07	0.07	-0.03	1	
6	ERROR TERMS	-0.02	0.01	0.02	-0.02	0.01	1

Source: own calculation

Table 37: Social Responsibility Model Efficiency Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*
1	ALBGNI	1					
2	FEMALE	-0.42	1				
3	NUMNEWBOR	-0.11	0.14	1			
4	SIZE_LN	0.24	-0.19	0.00	1		
5	PAR30	-0.01	-0.07	0.07	-0.03	1	
6	ERROR TERMS	0.02	-0.03	0.00	0.05	-0.02	1

Source: own calculation

Table 38: Social Responsibility Model Productivity Endogeneity Test

		1	*2*	*3*	*4*	*5*	*6*
1	ALBGNI	1					
2	FEMALE	-0.42	1				
3	NUMNEWBOR	-0.11	0.14	1			
4	SIZE_LN	0.24	-0.19	0.00	1		
5	PAR30	-0.01	-0.07	0.07	-0.03	1	
6	ERROR TERMS	0.00	0.00	-0.03	-0.02	0.02	1

Source: own calculation