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Development and Determinants of Credit Interest Rates of Microfinance Institutions

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Abstract. As millions of poor borrowers rely on microcredit products to finance various aspects of their lives, the price of such products cannot be rated important enough. This study analyzes the development and determinants of credit interest rates of microfinance institutions globally between 2005 and 2014. The purpose is to understand why interest rates vary so much in absolute level and development between world regions, countries and even within countries. To study the variation and find the determinants, a dataset from MixMarket containing 9,320 observations from 2,039 microfinance institutions is employed. First, the development of interest rates and major cost channels of microfinance institutions are scrutinized in a descriptive analysis. Second, in a fixed-effects econometric analysis the relationship between personnel expenses and interest rates and average salaries of microfinance institution employees and interest rates is studied. Findings suggest that with the increase of personnel expenses by one percentage point, portfolio yield (as proxy for interest rates) increases by 0.32 percentage points. When average salaries (measured in relative terms) increase by one unit, portfolio yield increases by 0.0248 percentage points. The study contributes by identifying personnel expenses as a major cost channel and average salaries as a major institution-specific factor of microfinance interest rates. Building on this, managers of microfinance institutions might want to assess to what extent and how they can reduce their personnel expenses. Furthermore, policy makers keen on improving the supply of affordable credit to the poorest of their population could focus on laying the foundations for microfinance institutions to have sufficient access to qualified human capital. This might ultimately benefit borrowers and stakeholders.

Keywords: Microfinance, Microcredit Supply, Interest Rates, Financial Development

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List of Abbreviations

ABC	Activity-Based Costing
ABM	Activity-Based Management
APR	Annual Percentage Rate
CAGR	Compound Annual Growth Rate
CGAP	Consultative Group to Assist the Poor
DEA	Data Envelopment Analysis
EAP	East Asia and the Pacific
ECA	Eastern Europe and Central Asia
EIR	Effective Interest Rate
FE	Fixed Effects
GDP	Gross Domestic Product
GLP	Gross Loan Portfolio
GNI	Gross National Income
IPO	Initial Public Offering
LAC	Latin America and the Caribbean
LLP	Loan Loss Provisions
MENA	Middle East and North Africa
MFI	Microfinance Institution
NBFI	Non-Bank Financial Institution
NGO	Non-Governmental Organization
OER	Operating Expense Ratio
OSS	Operating Self-Sufficiency
p.a.	per Annum
p.c.	per Capita
PAR	Portfolio at Risk
pp.	Percentage Point
ROE	Return on Equity
ROGLP	Return on Gross Loan Portfolio
SA	South Asia
SFA	Stochastic Frontier Analysis
SHF	Shareholder Firm
SME	Small and Medium Enterprise
SSA	Sub-Saharan Africa
USD	US-Dollar

1. Introduction

The global microfinance sector has grown substantially in the past years. The aggregate global gross loan portfolio (GLP) of microfinance institutions (MFI) grew by almost 24% p.a. during the years 2005 to 2014. The high growth rates were facilitated by a gradual commercialization of the sector (Cull et al. 2009a). As this paper shows, this commercialization has gone hand in hand with declining interest rates driven by a decrease of personnel expenses and average salaries paid by the MFIs.

The existing literature trying to explain determinants of interest rates focuses on operating efficiency of MFIs. However, surprisingly little research exists beyond the point of identifying operating efficiency as the important determinant of interest rates. This thesis aims to provide new insights into what part of operating efficiency drives interest rates. This thesis adds value to existing research by analyzing interest rates and their development using an extensive dataset with 9,320 observations from 2,039 MFIs based in 115 countries over a period of ten years. As outlined in section 4.2.1 in detail, nominal yield on gross portfolio (referred to as portfolio yield throughout this thesis) is used as a proxy for interest rates. Based on the discussed literature and descriptive evidence from the data set, the main hypotheses to test are:

H1: There is a highly economic and statistically significant positive relationship between personnel expenses of MFIs and the portfolio yield charged by MFIs.

H2: *There is a highly economic and statistically significant positive relationship between average salaries paid by MFIs and portfolio yield charged by MFIs.*

The developed hypotheses are tested in a two-way fixed effect regression approach to assess both cross-sectional and time-series dimension of the unbalanced panel. In addition, other important institution-specific and exogenous factors concerning interest rates serve as control variables in the empirical analysis. Findings confirm personnel expenses as the main influencing cost channel of interest rates and that higher average salaries paid by an MFI were associated with higher interest rates. The main benefit of the analysis is that it takes existing research, that mainly focused on operating expenses, one step further by identifying personnel expenses as the main driver of operating costs. In addition, findings suggest that average salaries could be the MFI-specific factor to analyze further concerning the variation of interest rates. These new insights pave the way for future research.

The interest in the topic was aroused after the author had experienced that annual interest rates for similar loan products charged by four different MFIs diverged between 30% and 45% in the same small town in rural Ghana. While developed countries are currently experiencing an unprecedented low interest rate environment for all types of credit, the most poor and vulnerable routinely pay 20% to 40% p.a. for their microloans, in many cases significantly more. Despite the controversy about microcredit interest rates and the high relevance of the topic, it is not fully understood why interest rates diverge so strongly between regions, countries, and institutions (Campion et al. 2010; Mersland & Strøm 2011; Roberts 2013). Since a better understanding of interest rates and their determinants might improve decisions by MFI managers and policy makers and might ultimately benefit borrowers and stakeholders, this represents a topic of utmost interest.

While microfinance used to attract mainly non-governmental organizations (NGOs), philanthropists, and development institutions, the past fifteen years have seen a rise of interest and engagement by the private sector (Rhyne & Christen 1999). This includes formal financial institutions, commercial funders, and even private equity funds. While social benefits were the driving force behind microfinance since the 1970s, the late 1990s and 2000s saw an increased focus on the financial sustainability of MFIs. This newer approach to microfinance is dominant today and stresses that MFIs should charge their borrowers interest rates, which are sufficiently high to cover all costs. MFIs working under this approach are able to survive without subsidies and their growth is no longer constrained by the limited availability of subsidies. Profitable MFIs furthermore attract more interest in microfinance which will lead to the entrance of new microfinance providers and thus to a further increase in outreach. Through the years, a competitive and efficient microfinance market with high quality financial products and low interest rates has developed. This thesis focuses on the supply view, thus looks at the MFIs rather than their clients. The corresponding demand side has been paid less attention to in existing research (Chowdhury 2009). Pollin (2007) states that micro-enterprises “need a vibrant, well-functioning domestic market itself that encompasses enough people with enough money to buy what these enterprises have to sell.” So far, no consensus exists on how big the global potential microfinance market is (Hes & Polednakova 2013).

Section 2 provides the literature background. Section 3 describes the data and contains descriptive statistics on various determinants of interest rates. Section 4 explains the empirical methodology. Section 5 outlines the empirical results and its limitations. Section 6 discusses the findings and concludes.

2. Literature Review

In this section, both descriptive and empirical evidence on potential determinants of interest rates is reviewed. These potential determinants can be specific to each single MFI or the country or the region, which the MFI works in. Yet today, surprisingly little descriptive and empirical evidence exist on what exactly drives the rates. Recently, the topic has gained in academic interest: Most empirical research on the topic has been published in the past five years and new methodological approaches are increasingly applied.

This section begins with a brief overview of cost and income of MFIs. Subsection 2.2.1 outlines existing literature on operating efficiency, personnel expenses and wages. Subsections 2.2.2 and 2.2.3 summarize literature on institution-specific and exogenous factors important in the context of interest rates.

2.1. Cost and Income

Interest income and fees are the main source of income for MFIs. They have to be demanded by MFIs to sustain their operations, since an MFI has to rent branch offices, pay its personnel, purchase office equipment, pay taxes, obtain refinancing, cover default costs etc. Operating costs are the most important of these cost drivers (Gonzalez 2007a). These, in turn, are made up mostly by personnel costs, as will be discussed later. However, there is little literature to be found examining in detail these operating and more specifically personnel costs. Even if the profit and loss statement shows how much is spent on staff salaries, it is not clear what processes and tasks are cost drivers by taking up staff time and other resources.

Brand and Gerschick (2000) authored an overview of how microfinance institutions should price their loans. They elaborate four methods which range from basic budgetary accounting to activity based costing (ABC) or management (ABM). MFIs following the latter methods have to break-down each single product into the activities, which go into producing it. At the end of this rather complicated and time-consuming process, MFIs are able to identify cost drivers and adjust their pricing for different products. Insights from such a process are shared from the Indian ICICI banker Nitin Agarwal (2006), who analyzes the Indian MFIs Share, Spandana and Asmitha following the ABC method. The three institutions apply group-lending methodology and thus have costs for forming the groups, holding the meetings, monitoring clients, and for overheads. Agarwal identifies the *sustaining activities*, which include travel, communication, infrastructure, human resources, fund raising, accounting and compliance, as main cost drivers. They are responsible for 37.3% of total costs. *Branch* expenses make up 32.7% and include e.g. administration activities, the handling of loan applications, and disbursements. The formation of groups is responsible for 3.9% of the total costs. The group meetings then incur costs through both non-financial activities (7.8%; including travel, member assembly, attendance record) and financial transactions (13.4%; including applications, disbursements, and repayment collections). 5% of total costs result from client monitoring (pre-disbursement check, monitoring, recovery). Looking at the same data from a different angle, Agarwal (2006) finds that throughout all above mentioned processes, IT and the management of information are the most important cost drivers (25.6% of total operating costs).

2.2. Determinants of Interest Rates

MFIs usually offer different credit products with different interest rates. Also within a product category, interest rates can vary according to the borrower's default risk and contract characteristics such as loan amount, collateral and tenor. It is thus not feasible to identify a common interest rate charged by MFIs. For this reason, and due to better data availability, portfolio yield is used as a proxy. Portfolio yield will be explained in more detail in subsection 4.2.1. It is calculated by dividing an MFI's financial income by its gross loan portfolio. Portfolio yield is not only affected by changes in the interest rates but also by arrears. Therefore, portfolio yield might underestimate the MFI's effective interest rates (EIR) by 5 to 6 percentage points (Gaul 2011). In line with literature, in this thesis it is assumed that the gap between effective interest rates and portfolio yields is constant and uncorrelated with the variation in the level of interest rates and differences in operating expenses. Thus, despite their differences, the terms portfolio yield and interest rate will be used synonymously in this thesis.

2.2.1. Operating Efficiency, Personnel Expenses and Wages

Efficiency and Productivity

Operating expenses make up the bulk of all costs of MFIs. In 2011, operating expenses accounted for 14% of the gross loan portfolio (global, weighted average) which translates into more than half of the portfolio yield of 26.9% (Rosenberg et al. 2013). The high importance of these costs explains why a strong focus on efficiency exists: To stay competitive, to gain a competitive advantage, or to improve profits, MFIs intent to trim down operating expenses and to improve the productivity of their assets and their staff. Efficiency and productivity are measured through a variety of indicators. Most prominent is the earlier introduced OER which divides operating expenses through the (average) gross loan portfolio and thus can also be expressed as costs per dollar of portfolio lent (Rosenberg et al. 2013). However, this indicator disadvantages MFIs with small loan sizes: As explained earlier, handing out many small loans is costlier than handing out a few larger loans. An alternative point of view grants the costs per borrower or costs per loan. MFIs which excel in this measure manage to reach out to a large amount of borrowers in a cost-effective way, e.g. through village banking or strongly standardized products. Rosenberg et al. (2009) caution that the comparability of these efficiency variables remains limited: For example, an MFI, which starts accepting deposits, might see a strong increase in its OER, even though its real efficiency has not decreased.

Insights in the operational structure of an MFI can be gained by the indicator loan officers per total staff.[1] It shows what percentage of staff is employed in the core business of the MFI. A growing middle and higher management can lead to a decrease of this ratio. It seems that mature MFIs have fewer loan officers per total employees than young institutions (Farrington 2000). The productivity of staff is measured with borrowers per staff member or borrowers per loan officer. Values for these indicators vary widely among MFIs (from single-digit to four-digit figures according to MixMarket data) and are heavily influenced by the credit methodology used (higher productivity for village banking and group lending, lower productivity for individual lending). Another way in which efficiency and productivity can be approached is by looking at the asset structure of an MFI. The Portfolio to Assets ratio shows how much of an institution's assets are allocated to the productive, income generating loan portfolio. Engaging in non-core activities or investing heavily in fixed assets can depress this ratio. Improvements in all mentioned efficiency and productivity measures should result in better over-all efficiency, which should then enable the MFI to reduce its interest rates or to improve its profitability. Empirical evidence is again limited but supports the case for efficiency. It suggests a positive relationship between OER and portfolio yield (Cotler & Almazan 2013; Campion et al. 2010), a negative relationship between Portfolio to Assets and both portfolio yield (Ahlin et al. 2011) and OER (Gonzalez 2007a), and a negative relation between borrowers per staff member and OER (Gonzalez 2007a). Some of the introduced efficiency measure will be re-introduced in section 4.2.3 as control variables.

Personnel Expenses

Personnel expenses are the most important component of operating expenses for the bulk of MFIs (Stephens & Tazi 2006, Gonzalez 2007a). Fernando (2006) describes microfinance as "still a labor-intensive operation" (p.2). While there is some research available on operating efficiency of MFIs and its effect on interest rates, the costs of labor in microfinance and their determinants have not been researched, to a great degree due to a lack of good data. Referring to the definitions of the Global Impact Investing Network (GIIN, 2017) components of personnel expenses include "wages, benefits, trainings and payroll taxes incurred by the organization during the reporting period". Existing research rather looks at the effects of microfinance on employment and wages, the so-called social efficiency of microfinance. Gonzalez (2007a) uses surrogate-proxies for cost of labor, namely literacy rates and

[1] Detailed information on indicators can be found in the Pocket Guide to the Microfinance Financial Reporting Standards Measuring Financial Performance of Microfinance Institutions (The SEEP Network 2010).

costs of other inputs (e.g. internet rates, cost of residential phone lines), but these proxies are hardly satisfactory.

The cost of human capital contains characteristics of both institution-specific and exogenous nature. For example, if two identical MFIs operate in the same country and one chooses to pay its employees better salaries, it will incur higher costs. It is possible, though, that a better salary or higher paying incentive schemes lead to higher staff motivation and thus to offsetting effects (McKim & Hughart 2005). MFIs with a large senior and middle management will - ceteris paribus - also incur higher costs, which they have to cover with a higher interest rate. Between countries and regions, there are substantial differences in the salaries of loan officers as well as other employees (Gonzalez 2007a). While the skills, which MFIs demand from its loan officers, do not vary too much across regions and institutions, the compensation the MFI pays its employees does. In countries with low educational levels, it is possible that there is a lack of skilled graduates to fill all positions. In other countries with good education levels but a lack of employment opportunities, MFIs receive dozens of applications for a single job offer. Known for low personnel costs are the South Asian countries, which also consistently report low interest rates (Gonzalez 2011; Stephens & Tazi 2006).

2.2.2. Institution-specific Factors

A wide variety of institutions offering microcredit exists, which further varies across regions. Just analyzing a single microfinance market can reveal a plethora of distinctive institutions labeled “MFI”. In a country such as Peru, there are NGOs, cooperative banks, non-bank financial institutions (organized as Edpymes or Financieras), rural and municipal saving banks, and full-fledged banks offering microfinance products (León Castillo & Jopen Sánchez 2011). Between but also within these groups different types of institutions can be found. While some MFIs offer solely credit products, others have expanded their offerings to savings, insurance, or leasing products. Some cater to the urban poor while others concentrate on the rural population. Microfinance banks such as Mibanco have expanded their offerings from financial products to poor entrepreneurs to small and medium enterprises (SME). There are new forms of microbanks emerging, for example, the greenfield banks that lead financial inclusion in SSA in the past ten years (Cull et al. 2015). Bearing this vast heterogeneity of institutions’ characteristics and business models in mind, institution-specific factors and their impact on interest rates play an important role for this paper’s analysis.

Legal Form

The legal form of an MFI appears to be a crucial factor for determining the interest rate on micro credits. According to Cull et al. (2009a), the highest interest rates are charged by NGOs while banks are able to offer their clients lower interest rates than both NGOs and non-bank financial institutions (NBFIs). This is especially due to the clients targeted by the different actors: NGOs routinely work with poorer borrowers, offer smaller loans, and have thus higher cost structures, as elaborated in the next section. Banks are more likely to provide funding to more affluent customers and SMEs, both of which usually can obtain lower interest rates. Mersland & Strøm (2008) look for differences between NGOs and shareholder firms (SHF; as most banks and NBFIs are) offering microfinance products. In contrast to the before mentioned study they find little evidence that differences exist with regard to commercial or social orientation. They argue that both SHFs and NGOs “are driven by the same economic rationality” (ibid, p. 19). Revisiting the topic with a less empirical approach, Mersland (2009) argues that there is not one dominant, advantageous legal form but that shareholder firms, cooperative institutions, and non-profit organizations should continue to coexist. While NGOs have cost advantages in some areas, e.g. by being less exposed to asymmetric information problems with borrowers, depositors, and donors, shareholder firms have advantages when it comes to ownership costs which include e.g. monitoring costs, costs of managerial opportunism, and access to equity capital. In a further study, Mersland & Strøm (2011) find no significant impact of an SHF status on portfolio yield. Jia et al. (2016) find no impact on interest rates in their case study examining the commercialization of China's largest MFI in NGO form. Using Data Envelopment Analysis (DEA) on a data set of 39 MFIs offering both microcredit and microsavings services, Haq et al. (2009) do not find an institutional type with clear advantages in efficiency. In a relatively new study, D'Espallier et al. (2017) examine the transformation of 66 MFIs from NGO to a shareholder-owned and typically regulated financial entity. They find a drop of portfolio yield by 3.9 percentage points, which they mainly link to a cut in operating expenses by 1.1 percentage points.

For-Profit vs. Non-profit

Compared to their non-profit peers, profit oriented institutions should, ceteris paribus, be more interested in higher yields in order to earn sufficient profits for their owners. Non-profit organizations lack this motive, as all profits have to remain within the organization. However, non-profits that wish to grow must have sufficient funds to do so. Even if they aim to expand by the help of external borrowings rather than internal financing, they have to make sure that their equity makes up a sufficient share of their balance sheet. Given the limited availability of donor funds, also NGOs can thus have a strong motive for earning high profits (Rosenberg et al. 2009). Concerning operational efficiency and cost structures, several conflicting channels arise. It is assumed that for-profit institutions receive higher pressure from their owners to improve operational efficiency. In the meantime, for-profits are usually more rigorously regulated which incurs certain additional costs for an organization. Empirical evidence on the comparison between for-profit and non-profit institutions is provided solely by Roberts (2013). He finds that, after controlling for a variety of institution-specific variables, for-profits charge indeed higher interest rates. However, these higher yields do not translate to higher profits, as for-profit-organizations bear significantly higher cost structures than NGOs.

Depth of Outreach

Two measures are commonly applied to observe to what extent an MFI focuses on the marginalized population: the average loan size and the share of female borrowers. Concerning average loan size, the logic is that poor borrowers receive comparatively small loans. This in turn implies that an MFI with a low average loan size succeeds in reaching out to the poor. This comes, however, at a cost: There is widespread consensus that it is expensive to provide small loans and that to cover these high costs, MFIs have to charge high interest rates (Rosenberg et al. 2009). The rationale behind this theory is straightforward: It requires far less effort to provide and collect a single loan of a given amount then to disburse the same loan amount in hundreds of small loans and then engage in collecting these. Due to certain fix costs per loan, a small average loan size will drive up average costs given a certain portfolio size (Conning 1999, Brand & Gerschick 2000, Cull et al. 2009a). Encompassing descriptive evidence is recently complemented by supporting empirical research (Ahlin et al. 2011, Cotler & Almazan 2013, Roberts 2013, Hermes et al. 2009, 2011, Mersland & Strøm 2011). Gonzalez (2007a), however, cautions that the effect decreases with higher loan sizes. In an analysis of the Latin American microfinance market, Campion et al. (2010) find suggestive evidence of operating efficiency decreasing again above an average loan size of USD 1,800.

It is argued that women usually take smaller loans (Campion et al. 2010) and that targeting women is linked with reaching out to poor borrowers (Hermes et al. 2011). This would translate to higher interest rate and higher operating costs. However, empirical evidence is mixed. Roberts (2013) finds a higher share of female borrowers corresponding with higher interest rates. Bos & Millone (2012) furthermore find positive impacts of the share of female borrowers on operating costs. Hermes et al. (2009, 2011) note that a higher share of female borrowers correlates with lower efficiency measures. On the other hand, Assefa et al. (2013) find no significant effects on interest rates. The same applies to the study of Campion et al. (2010), who do however find weak but positive effects on operating expenses. Since it is often NGOs who wish to reach out to female borrowers, it is possible that these NGOs have higher operating costs but refrain from charging higher rates.

Portfolio Quality

The case for portfolio quality influencing portfolio yield is ambiguous. If an MFI has low repayment rates, it is affected through two main channels. First, the MFI has losses of interest income because of borrowers not adhering to their contractual obligation. Either the MFI can accept lower profits or it can raise its interest rates so that the higher income from the performing loan portfolio offsets the MFI's loan losses. If the MFI does not increase interest rates, its portfolio yield declines, since this indicator puts into proportion total financial income with the gross loan portfolio. If the MFI adjust its rates, the non-defaulting borrowers have to pay higher interest rates, however the portfolio yield might remain unchanged, given the loss of interest income from the delinquent borrowers. The second channel concerns operating costs: If an MFI has a high number of non-performing loans and wishes to recover these, it needs to spend high efforts on these recovery activities. This increase in operating costs can again pressure the MFI's management to raise interest rates. Empirical evidence on the topic is limited. Campion et al. (2010) finds insignificant and Mersland & Strøm (2011) significant negative effects of delinquencies (measured by PAR30) on portfolio yield. Campion et al. (2010) finds also positive, insignificant effects on the Operating Expense Ratio[2] (OER). Other empirical evidence (using stochastic frontier analysis, SFA) suggests a negative influence of non-performing loans on efficiency measures (Bos & Millone 2012). Addressing the topic the other way around and thus showing a possible channel of reverse causality, Assefa et al. (2013) find significant positive effects of the portfolio yield on the write-off rate (but not on the portfolio quality indicators PAR30 and PAR90): An MFI charging high interest rates might thus need to bear higher default rates.

Several indicators can measure portfolio quality of MFIs. Prominent are the Portfolio at Risk greater than 30 days (PAR30) and 90 days (PAR90). They show what percentage of the GLP has been in arrears for more than 30 or 90 days, respectively. The percentage of GLP, which is written off during a year, is captured by the write-off ratio. Loan loss provision (LLP) expenses show how much an MFI sets aside for potential loan losses in a given period on a net basis. The provision expense ratio expresses these expenses as a percentage of GLP. This latter indicator is predominantly used in this thesis.

[2] The Operating Expense Ratio is obtained by dividing operating costs through the gross loan portfolio of an MFI. An MFI with a low OER is –ceteris paribus- operationally more efficient than an MFI with a higher OER.

Funding Costs

Financial expenses on borrowings and deposits are an important cost driver for microfinance institutions. According to Rosenberg et al. (2013), funding expenses accounted for 7.8% of the GLP in 2011 and thus made up more than a quarter of portfolio yield. An MFI with elevated funding expenses must, ceteris paribus, demand higher interest rates from its borrowers or accept reduced profitability. This reasoning finds limited but unchallenged support from empirical analysis (Cotler & Almazan 2013; Campion et al. 2010; Mersland & Strøm 2011).

Profitability

There are many institutions in the microfinance sector, which offer low interest rates, show unimpressive profitability measures, and remain functioning only with the help of subsidies (cf. D'Espallier et al. 2013). Meanwhile, the controversy around the Mexican MFI Compartamos was fueled by the exorbitant profits of this MFI while charging interest rates significantly higher than the Latin American average: For 2005, it reported a portfolio yield of 86% and an ROE of 55% (Rosenberg 2007). Generally, MFIs aiming to improve their profitability or to reach certain goals (e.g. OSS > 100% or ROE > 10%) must either lower their costs or increase their income. From these and many more examples, it can be inferred that MFIs with good profitability measures are likely to charge higher interest rates than MFIs with low profitability measures. However, too high interest rates can lead to reduced customer demand, as studies on demand elasticity have shown to various degrees (Karlan & Zinman 2008; Dehejia et al. 2012; Demirgüç-Kunt et al. 2008; Fafchamps & Pender 1997). This reduced outreach can mean the sacrifice of scale effects and thus lower profits. Even more problematic might be adverse selection effects, which expensive MFIs might have to deal with, especially in competitive microfinance markets (Demirgüç-Kunt et al. 2008; Armendáriz & Morduch 2010). These adverse selection effects can result in high defaults and thus low portfolio yield. Empirical evidence suggests that the harmful effects are not strong enough to offset the direct effect of increasing the interest rate: Evidence points towards significant, positive effects of profitability on portfolio yield (Cotler & Almazan 2013). However, this effect might be limited to MFIs engaging in individual lending (Cull et al. 2007). For Latin America, Campion et al. (2010) find a significant, positive relationship between OSS and portfolio yield and a significant, negative relationship between OSS and OER.

Scale Effects and the Learning Curve

A reduction in operating expenses could occur due in MFIs obtaining *scale* and experience effects. An MFI, which successively adds more borrowers, can distribute its overhead costs on an increasing number of loans. Thus, every loan has to finance less and less of overhead costs and interest rates can be gradually reduced. However, the size of scale effects in microfinance is debated and evidence dampens the potential for cost redcutions. As an institution grows from a small NGO to a full-fledged bank, it will add more overhead functions, has to comply with stricter rules and regulations, offers more products, which increases complexity of operations. Scale is usually measured by the total assets, GLP, or the number of borrowers. Roberts (2013) and Mersland & Strøm (2011) find evidence of negative effects of total assets on portfolio yield. The effect of the number of borrowers has been scrutinized more often: Links are found to lower interest rates (Ahlin et al. 2011; Roberts 2013) and the efficiency of an organization (Hermes et al. 2009). Gonzalez (2007a) finds a negative relationship to OER, warns however of diminishing scale effects: Already with a client base of 2,000 borrowers, an

MFI might have little more scale benefits to expect. A possible explanation is that microfinance is a labor-intensive business. Salaries make up most of the costs while fixed costs are of comparatively small importance (Rosenberg et al. 2009). The result of Gonzalez (2007a) is seconded by Campion et al. (2010).

Next to size, *age* of an MFI might also be an important determinant of microcredit interest rates. Over the years, an MFI can constantly improve its processes and organization and can cut unnecessary costs. The staff employed by the MFI becomes more experienced and productive. The MFI learns more about the market it is operating in, collects information on its borrowers, and might bind an increasing number of loyal clients to the organization. Support of this reasoning is found in the literature: reported are beneficial age effects on interest rates (Campion et al. 2010; Mersland & Strøm 2011; Nwachukwu & Asongu 2015) and beneficial but diminishing effects on the OER (Gonzalez 2007a). Other evidence, however, is mixed: Roberts (2013) does not find significant effects. In their stochastic frontier analyses, Hermes et al. (2009; 2011) find harmful effects of age on the organizations' efficiency. They argue that new MFIs can use the lessons learned from the incumbents and built highly efficient institutions from scratch, while older MFIs might be more reluctant to change practices.

Regulation

Regulation can affect microcredit interest rates in different ways. Regulated institutions (such as banks) might bear higher costs due to extensive regulation and will thus demand higher interest rates to cover these costs. Regulation, however, can also put downward pressure on interest rates either by setting interest rate ceilings or by enforcing pricing transparency. In the latter case, the regulator can prohibit charging hidden costs or demand public disclosure of all interest rates, thus making it easier for borrowers to engage in interest rate shopping. Rosenberg et al. (2013) provide descriptive evidence of regulated MFIs charging lower interest rates than non-regulated MFIs (which might depend to a large degree on the smaller loan sizes of non-regulated MFIs). Roberts (2013) finds in his empirical analysis a weak and unstable but negative relationship to portfolio yield. Khalily et al. (2014) show in their examination of regulation in Bangladesh a robust positive impact of imposed regulation on cost efficiency of MFIs. To the contrary, Nwachukwu and Asongu (2015) detect a significantly higher average portfolio yield within formally regulated micro banks compared to their peers.

2.2.3. Exogenous Factors

The success of an MFI depends to a large degree on the environment in which it operates and thus numerous exogenous factors may play a role in determining the level of interest rate for microcredits. This can be seen, for example, in microfinance holdings, which operate MFIs with the same mission, approach, methodology, and equipment in various countries. In 1999, Frankfurt based ProCredit Holding opened three MFIs in Eastern Europe and the Caucasus, namely in Albania, Georgia, and Kosovo. In 2011, ProCredit Bank Albania earned its owners an ROE of just 2.8% while Georgia earned 15.8% and Kosovo even 24.8%. In the same year, the portfolio yields of the nineteen ProCredit institutions reporting to MixMarket ranged from 11.8% in Bosnia-Herzegovina to 31.9% in the Democratic Republic of Congo. Factors, which differ between world regions and countries or even within countries, can have significant impacts on interest rates charged by MFIs. Thus, it is important to include those factors in any attempt to determine drivers of interest rates. This review of literature shows that, despite the importance of these exogenous factors, research and evidence is limited.

Region and Country

Interest rates vary strongly between the different world regions. This topic is addressed in detail by Rosenberg et al. (2009) and - to a lesser degree - in the follow-up (Rosenberg et al. 2013). The latter study identifies SA and ECA as the regions with the lowest interest rates while the Middle East and North Africa (MENA) and LAC take the top spots. Vast declines in interest rates are found in the less developed microfinance markets of SSA (from 39% in 2004 to 25% in 2011) and EAP (35% to 26%). As a result, average regional portfolio yields have declined and the differences between the regions decreased: In 2004, the median portfolio yields of the six regions ranged from 28 – 39%, in 2011 from 21 – 30%. Cotler & Almazan (2013) prepare separate regressions for the three regions Africa, Asia, and America. They find efficiency advantages for Asian MFIs especially compared to African MFIs. Using SFA, Hermes et al. (2009) find corresponding efficiency deficits for African MFIs, even though their findings are not robust.

However, focusing on the world regions might not be sufficient. Even within regions, there are substantial differences between the countries. LAC, for example, encompasses Bolivia and Ecuador, which are known for very low interest rates, as well as Mexico, which is home to several of the world's most expensive MFIs (MIX 2012). This topic will be addressed in more detail in the descriptive analysis of subsection 3.2.

Macroeconomic Environment

It is contested to what degree MFIs, and the microentrepreneurs they cater to, are affected by a decline or expansion of their country's economy. Ahlin et al. (2011) outline three pathways through which the growth of the gross domestic product (GDP) p.c. could potentially affect MFIs performance: First, the small, local markets in which MFIs operate could be detached from the country's overall economic development. Second, the growth of the economy could increase domestic demand, spur investments, and foster optimism and risk-taking of micro-entrepreneurs. Third, high growth rates could harm MFIs as the clientele can move on to take salaried jobs and the informal sector declines. Case studies of MFIs and countries exist which hint at the resilience of MFIs in time of crisis. Patten et al. (2001) analyze BRI from Indonesia and find strong repayment records from micro-borrowers during time of crisis while the corporate, SME, and retail credit portfolios caused substantial loan losses for BRI. The authors attest this to contract design (installment loans), the engagement of micro-entrepreneurs in the production and trading of essential products and services, the remoteness of the rural sector from the Indonesian monetary crisis, and the microborrowers' high appreciation of BRI's services. Empirical support for these findings is provided by Gonzalez (2007b) and his fixed-effects regression on 639 MFIs: He does not find a significant relationship between the growth rate of GNI p.c. with most portfolio quality measures. In another study, he finds no significant relationships between macroeconomic variables (including the absolute level of GNI p.c. and inflation) and OER, except for negative effects of lagged GNI p.c. growth (Gonzalez 2007a). The study from Ahlin et al. (2011), however, identifies a clearer relationship between macroeconomic and institutional performance for MFIs and a significant linkage between GDP p.c. growth and portfolio quality. Nonetheless, a significant link between economic growth (or the absolute level of GDP p.c.) and portfolio yield is not found in this study. On the other hand, inflation is found to be positively linked with portfolio yield. Ahlin et al. (2011) argue that MFIs demand from their clients an inflation premium to avoid potential harmful effects. The cost base of MFIs is also affected by higher inflation rates, presumably through elevated funding expenses.

Financial Development and Financial Infrastructure

Financial development characterizes the degree to which a country has been penetrated by (formal) financial institutions and services. Financial development can be measured by various aspects and proxies. As an example, the World Bank distinguishes between measures of depth, access, efficiency, and stability of financial systems and looks at both financial institutions and financial markets (World Bank 2015). Countries with high financial development are characterized by a stable financial sector in which a variety of banks, insurance companies, leasing companies, brokers etc. participates. Basic financial instruments are offered to each individual while high net worth individuals and companies can access more advanced financial services. In a financially high-developed country, financial institutions work more efficient and can therefore offer better conditions for their products. Microfinance has grown and flourished in countries such as Bolivia, Bangladesh, Cambodia, or Kenya, while important and successful MFIs are nowhere to be found in the highly developed countries of Continental Europe or North America (cf. MIX 2011). Starting from blank in a country without basic financial development, however, might also pose challenges. Financial literacy might not be wide spread and MFIs will have difficulties in attracting local funding sources. It might also be a challenge to obtain qualified personnel; expensive trainings will be required, leading to higher operating expenses. High microcredit interest rates might be the consequence due to the lack of competition from formal banking. Ahlin et al. (2011) observe indeed a significant, negative relationship between financial development (measured as private credit / GDP) and portfolio yield, as well as positive effects of financial development on default and operating costs. Gonzalez (2007a) does not find a link between OER and the (not specified) variable of financial depth. Cull et al. (2009b) note that in countries with higher financial development MFIs tend to focus on the bottom segment of the market. This should in turn put upwards pressure on interest rates. In their paper on financial development and MFI efficiency, Hermes et al. (2009) reach the conclusion that “more developed financial systems create more efficient MFIs” (p. 20).

Credit bureaus are also related to financial development. Well-functioning, comprehensive, and accessible credit bureaus can offer cost advantages to MFIs by supporting the MFI in identifying unreliable borrowers and creating new incentives for borrowers to repay. The MFI thus saves money in the loan assessment process and by avoiding defaults and the related, expensive recovery processes. Gonzalez (2007a) confirms the expected beneficial effects of credit bureaus on the OER.

Microfinance Competition

One recurring theme in the debate on microcredit interest rates is the effect of competition. Following basic economic theory, it is expected that with growing competition and market saturation the interest rates of MFIs will decline to the benefit of the borrowers (Armendáriz & Morduch 2010). Competition can be advantageous in putting pressure on interest rates, expanding the market, and improving product quality, but it can also do harm, as Armendáriz & Morduch (2010) note: Clients might lose the incentive to repay as alternative funding sources become available (a problem which is linked to the repeated lending incentive). Furthermore, saturated markets are prone to over indebtedness and the worsening of portfolio quality (Armendáriz & Morduch 2010; Morduch 2013). In a report by CGAP, Porteous (2006) identifies four phases of competition. In the pioneer phase, a MFI is established in a new market. During take-off, new actors emerge and better products and services are offered, even though the pricing remains a minor issue. In the consolidation phase, the market becomes saturated and growth slows down. Segmentation in successful and less successful market participants can be observed and price competition starts. During the mature phase, several market leaders compete with their brand: Some MFIs focus more on quality and services; others compete mainly with low pricing. Accepting this model means changing expectations on competition effects: higher competition does not necessarily mean lower interest rates. Instead, price competition will be observed only at a late stage of market maturing and might not be open-ended. While descriptive research overwhelmingly stresses the negative effects of competition on interest rates (e.g. Helms & Reille 2004; Fernando 2006; Porteous 2006; Rosenberg et al. 2009), empirical evidence is more mixed: For Latin America, the downward pricing pressure from higher competition is found (Campion et al. 2010) while other studies fail to find a link (Cotler & Almazan 2013; Roberts 2013; Mersland & Strøm 2011). Assefa et al. (2013) do not assess portfolio yield or operating expenses as dependent variable, but find an increase in competition linked with deteriorating financial performance. However, the absence of clear empirical evidence is possibly resulting from the difficulty of assessing the level of competition. Variables used include the share of adult population using microfinance (Campion et al. 2010; Cotler & Almazan 2013), the Lerner index[3] (Assefa et al. 2013), and the number of MFIs in a country which report to MixMarket (Roberts 2013). While all proxies expose weaknesses, especially the last one is questionable: For example, Russia (106 MFIs) and China (76) would receive higher competition scores than the mature markets of Peru (72), Ecuador (58), and Bolivia (28): a result, which few market observers would agree to.

Other Factors

Density of population is expected to have beneficial effects on OER, an assumption that is confirmed by Gonzalez (2007a): It is easier and cheaper to reach a large number of borrowers in densely than in sparsely populated areas. It is assumed that through this channel of operating costs also negative effects on the portfolio yield can be observed.

Operating in a society marked by high *inequality* can affect an MFI. Such societies might make it difficult for micro-entrepreneurs to succeed or they might incentivize MFIs to focus on the base of the pyramid, which can result in elevated costs (Ahlin et al. 2011). At the same time, MFIs might have to pay high

[3] The Lerner Index is a measure of market power, calculated by dividing the difference between market price and marginal costs by the marginal price. A high value means that the firm (=the MFI) has high market power.

wages to attract skilled employees (Roodman & Qureshi 2006). Ahlin et al. (2011) use the GINI coefficient as proxy and find it positively linked with default rates, operating costs, and interest rates, and negatively linked with sustainability.

Presumably, the *physical infrastructure* of a country might also influence operating costs of an MFI and thus its interest rates. MFIs will have higher costs if the road network makes it difficult to reach borrowers, if the power supply is unreliable, or if clients cannot be reliably reached by phone. Yet, Gonzalez (2007a) does not find a significant relationship between physical structure indicators and the OER.

The *business environment* and the quality of *governance and institutions* are also likely to affect MFIs through various channels. In order to account for these qualitative factors empirical studies make use of indices and rankings such as the World Bank's Doing Business Indicators (Cotler & Almazan 2013; Ahlin et al. 2011; Gonzalez 2007a), the Worldwide Governance Indicators (Roberts 2013; Assefa et al. 2013; Ahlin et al. 2011), and the Heritage Foundation's Index of Economic Freedom (Mersland & Strøm 2010). While there is an overlap between the mentioned indicators, there are two main approaches. Stylized, the Worldwide Governance Indicators (WGI) give information about the governance in a state: They judge how well the government functions and the rights of the inhabitants are protected. The Doing Business Indicators and the Index of Economic Freedom have a more narrow view: They assess factors, which affect people and firms engaging in business activities.[4] However, most of the above-mentioned studies either use these proxies as instrumental variables and do not report their effects, or they do not analyze portfolio yield and operating expenses as dependent variables. Gonzalez (2007a) does not find a relationship between the two Doing Business indicators *legal rights* and *credit information* and the OER. Ahlin et al. (2011), meanwhile, find several Worldwide Governance Indicators and Doing Business variables to be linked with higher operating costs. They theorize that the existence of *functioning* institutions and thus the need to comply with their regulations might mean extra costs for MFIs, which offset the various benefits.

3. Data, Descriptive Analysis and Hypotheses

This section contains two subsections. It begins with subsection 3.1 that provides information on the data used in both the descriptive and the empirical analysis. Subsection 3.2 contains the descriptive analysis on microfinance interest rates, their development, and major cost channels.

3.1. Data

The data on microfinance institutions is obtained from MixMarket, a database to which more than 2,400 MFIs have voluntarily reported their financial data and/or social information in the past years. The data is self-reported and thus prone to error. To counteract reporting errors, a review system and quality checks by MixMarket are employed. Commercial-oriented MFIs and MFIs wishing to attract cross-border funding are more likely to report to MixMarket than small microcredit programs, which are operating with local resources. Successful, profitable MFIs are also more likely to report than loss-

[4] More information can be found on the respective websites: info.worldbank.org/governance/wgi/ ; doingbusiness.org/ ; http://www.heritage.org/index/. Assessed February 06, 2017.

making institutions (Cull et al. 2009b, c). In spite of data quality issues and the inherent self-selection bias, the MFIs covered in MixMarket collectively command over a very high percentage of both the total assets and the customer base of the worldwide microfinance market (Rosenberg et al. 2009). Thus, MixMarket data gives a good picture of the microfinance market as experienced by the typical microfinance borrower.

Only annual information is used in this thesis, thus quarterly observations are removed from the data set. This decision is taken because the majority of institutions report only annual data and the focus on quarterly data would have left out a large number of MFIs. In addition, all observations outside the period 2005 – 2014 are excluded. The start year is chosen to mirror the period where the number of MFIs reporting to MixMarket increases and therefore increase representativeness. In addition, with this choice several years before the outbreak of the global financial crisis are included, which allows for determining an effect of the crisis. Since a quite large number of MFIs show a time lag in reporting their figures and correct already reported data later on, 2014 is chosen as the end year of the sample to maximize quality and quantity in the reported data. Thus, it was not deemed feasible to include the years 2015 and 2016 in the sample. Observations were excluded when MFIs reported twice for the same fiscal year to avoid ambiguities, which applies to ten MFIs. The data set further excludes all observations, which do not include information on portfolio yield.

Following Rosenberg et al. (2013), all annual information provided by two major institutions Harbin Bank (China) and VBSP (Vietnam) is removed. Both institutions report a large loan portfolio of between USD 6.0 to 13.1 billion with only parts of the portfolio targeted at microfinance. Thus, they report financial characteristics, which cannot be attained by regular MFIs without major (cross-) subsidization. The scale of these two MFIs increases the likelihood that their opaque financial reporting to MixMarket can skew the results of this analysis.[5]

After these adjustments have been made, a data set of 2,039 MFIs remains. The MFIs in the sample reported between one to ten years of annual information between 2005 and 2014, yielding to 9,320 annual MFI observations. The reporting MFIs are based in 115 countries. Due to the quality and quantity of the sample, it is considered to be representative for the global microfinance market.

The data source for all macroeconomic variables that are added to the data set as control variables is the World Bank's World Development Indicators database.

3.2. Descriptive Analysis

The descriptive analysis aims to give an encompassing overview of the development of interest rates. It takes a closer look at the five major channels through which portfolio yield of MFIs can be influenced: personnel expenses, funding costs, provisioning expenses, administrative expenses (including depreciation and amortization) and profits. For descriptive analysis the sample is split into several peer groups. The most important peer groups are made up by the world regions and by the different legal statuses. Further characteristics of interest are profit status, regulatory oversight, sustainability, age, scale, and target markets. The differentiation makes it possible to gain insights in how interest rates differ e.g. between regions or between regulated and unregulated MFIs.

[5] For more details on these two institutions, please refer to Rosenberg et al. (2013, pp.24-25).

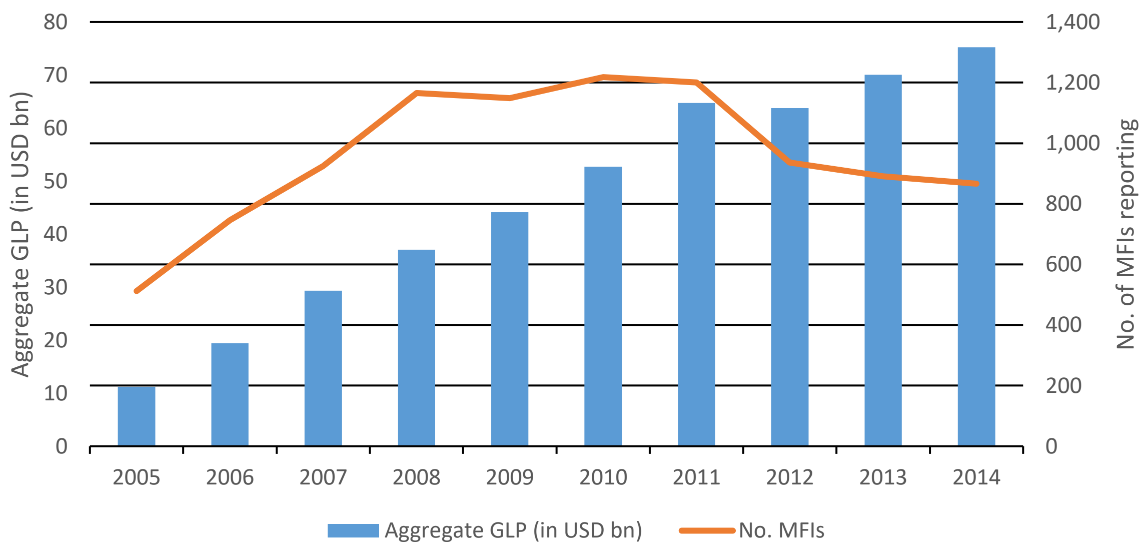
The so far most comprehensive, descriptive analyses of microcredit interest rates were published by CGAP (Rosenberg et al. 2009, 2013). These two studies serve as cause for thought for this descriptive analysis. However, the data set used in the 2013 paper looks at the timeframe 2004-2011 and is based on more than 3,000 observations less than this thesis. Therefore, caution is advised for direct comparisons between the two analyses.

The descriptive analysis is divided into three parts. Subsection 3.2.1 describes the data set in more detail. Subsection 3.2.2 reports the level and the development of microcredit interest rates. Finally, subsection 3.2.3 gives an overview of the components of interest rates.

3.2.1. Sample Description

Global. The data set contains annual information of MFIs from the years 2005 to 2014. The number of MFIs reporting increases until it peaks in 2010 and then declines until 2014 (Figure 1). During the period under observation, the reported nominal loan portfolios have increased manifold. In 2005, 512 MFIs reported an aggregate portfolio of USD 11.1 billion, in 2014 there were 866 MFIs reporting an aggregate portfolio of USD 75.2 billion. This enormous growth with a compound annual growth rate (CAGR) of 21 % is due to the increased popularity of MixMarket, the high growth rates of existing MFIs, as well as the establishment of new institutions. As anticipated by Jansson (2001), a prerequisite for this growth has been the transforming of MFIs into deposit-taking institutions and a better availability of both local and international financing.

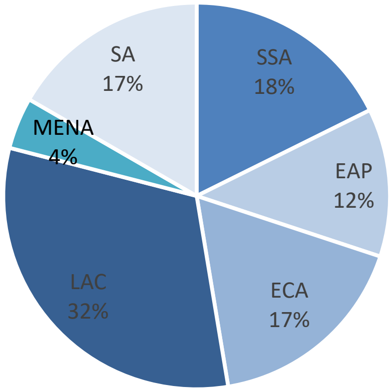
Figure 1: Reporting MFIs and Aggregate GLP



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes all 9,320 observations of the data set from 2005 to 2014.

Regions. In the sample, Latin American MFIs are responsible for almost a third of the observations (Figure 2). The MENA region, meanwhile, accounts for only 4% of observations but has also the lowest population among the six regions. It can be debated whether this distribution corresponds with the reality of microfinance in the past years. If the focus is put on the client level, the SA region should be represented more prominently: With the large client base especially of Indian and Bangladeshi MFIs, SA accounted for 58% of microfinance borrowers in MixMarket during 2014 (Table 1). Shifting the view, however, to the GLPs of the MFIs, the importance of SA dwindles: its share of the global GLP is in total 14% compared to 51% for Latin American MFIs. Due to high loan sizes in ECA, the region accounted for only 3% of borrowers but 11% of GLP in 2014.

Figure 2: Regional Distribution (2005 – 2014)



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes all 9,320 observations of the data set.

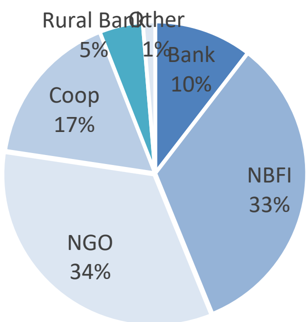
Table 1: Regional Distribution of Sample (2014)

	SSA	EAP	ECA	LAC	MENA	SA
by number of MFIs	20%	13%	12%	35%	3%	17%
by number of borrowers	5%	8%	3%	23%	2%	58%
by aggregate gross loan portfolio	14%	8%	11%	51%	1%	14%

Source: Author's rendering of MixMarket data (2014).
Note: Includes all 866 observations of the data set.

Legal Status. More than two thirds of observations belong to NGOs and NBFIs; banks (10%), rural banks (5%), and cooperatives and credit unions (17%) are represented to a lower extent (Figure 3). Over the years, the share of reporting cooperatives has more than tripled while the share of banks and NBFIs has only increased slightly. This latter observation is surprising when one takes into account the calls for formalization and the

Figure 3: Distribution by Legal Status (2005 – 2014)



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes all 9,320 observations of the data set.

transformations from NGOs to NBFIs and banks. Again, proportions change when not the number of banks and NBFIs is considered but their share of the overall loan portfolio (Table 2). Often, regulation demands a certain minimum equity to transform into a NBFI or bank, which makes it difficult for small institutions to upgrade. Meanwhile the bigger NGOs see high advantages in transformation, e.g. to allow the influx of private equity capital or to be able to offer more products such as savings accounts and insurances (Frank 2008).

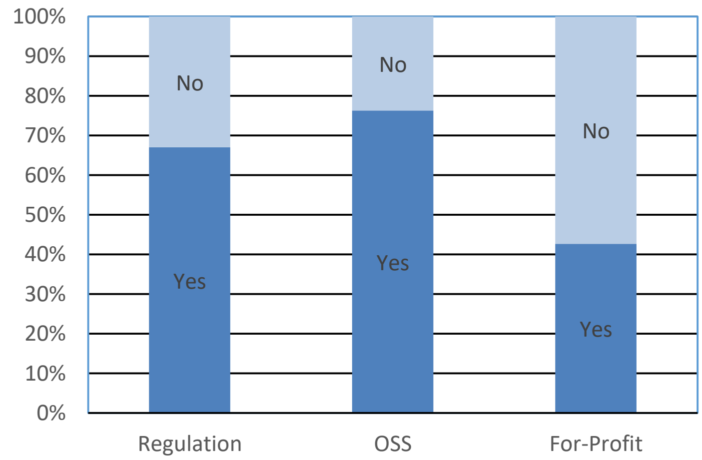
Table 2: Distribution of Sample according to Legal Status (2014)

	Bank	NBFI	NGO	Coop	Rural Bank	Other
by number of MFIs	11%	38%	30%	18%	1%	2%
by number of borrowers	16%	44%	36%	2%	1%	0%
by aggregate gross loan portfolio	42%	31%	12%	14%	0%	0%

Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes all 9,320 observations of the data set.

Other characteristics. Over the whole sample 67% of MFIs are regulated, coming from 65% in 2005 to 70% in 2014 (Figure 4). Operational self-sufficient (OSS)[6] MFIs make up 76% of observations. In 2005, their share was 81% and came down to 79% in 2014. Interestingly, sustainability does not seem to depend on the orientation of the MFI as a for-profit or non-profit organization: 77% of for-profits and 81% of non-profits operated sustainably in 2014. As for the distribution into for-profits and non-profits, the number of observations from for-profits (43%; Figure 4) trails the non-profit observations (57%).

Figure 4: Distribution by Regulation, Operational Self-Sufficiency, Profit Status (2005 – 2014)



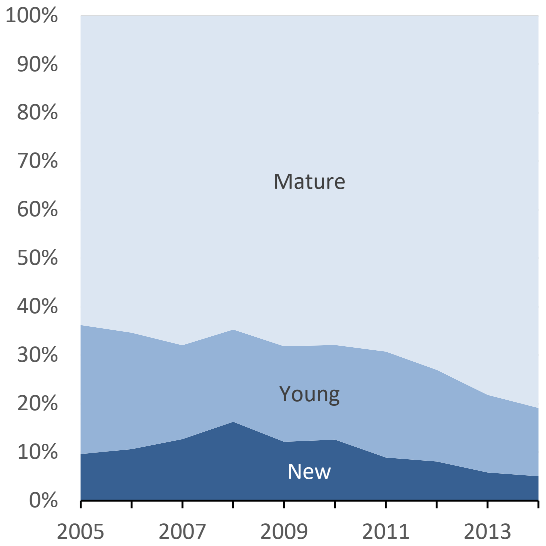
Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes all 9,320 observations of the data set.

Over the whole sample, mature MFIs (>8 years old) make up the majority of observations (70%), followed by young (5-8 years; 20%) and new MFIs (0-4 years; 10%). Figure 5 shows the shifting proportions over the years, providing the picture of a maturing sector where new entrants are slowly

[6] The OSS is obtained by dividing operational income by the sum of operational, funding, and provisioning expenses. An OSS > 1 means that the MFI can cover its costs from its operational income. Thus, it is operational self-sufficient and deemed sustainable.

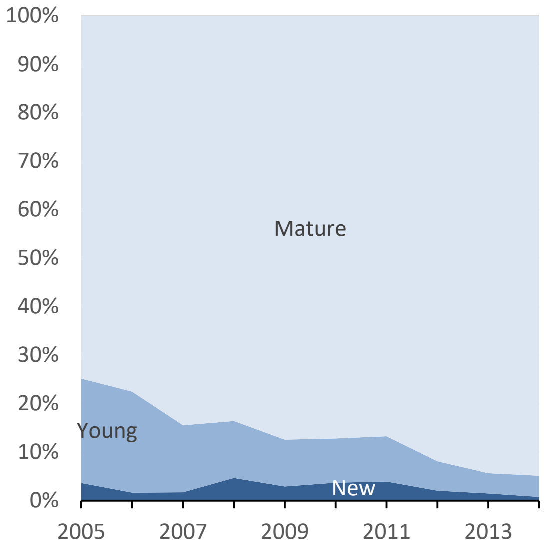
becoming a rarity. This development becomes even more notable when the amount of the GLP is considered (Figure 6).

Figure 5: Distribution by Age (Number of MFIs)



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes all 9,320 observations of the data set.

Figure 6: Distribution by Age (Aggregate GLP)



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes all 9,320 observations of the data set.

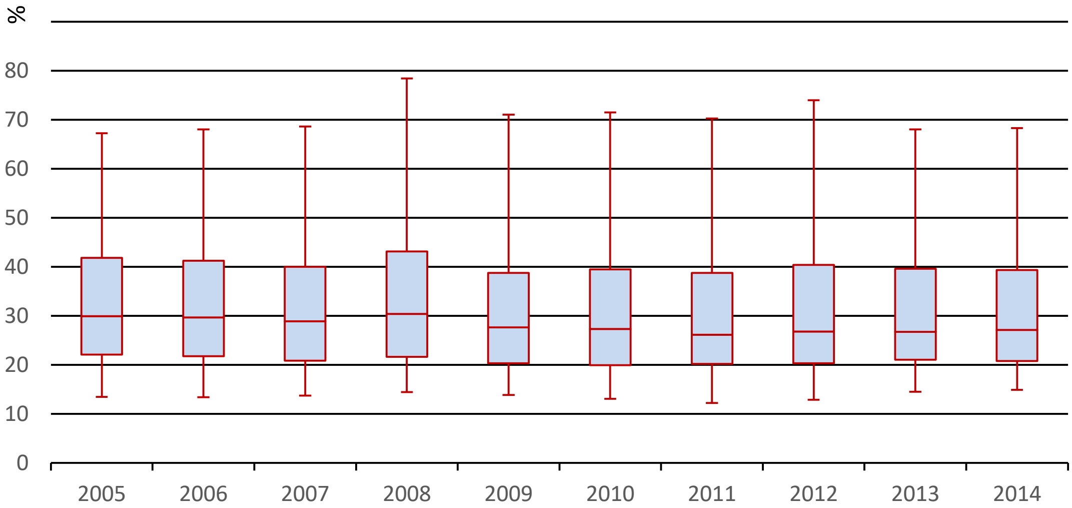
3.2.2. Level and Development of Interest Rates

Global. In 2014, the global median interest rate charged by MFIs was 27.1%[7] (Figure 7). 5% of MFIs demanded interest rates of 14.9% and below from their clients while another 5% of MFI charged interest rates in excess of 68.3%. 50% of MFIs reported portfolio yields between 20.8% and 39.4%.

In the course of the observed years, the median portfolio yield decreased globally from 30.0% in 2005 to 27.2% in 2014, which corresponds to an annual decline of 1.0 percentage points. Substantial decreases can also be seen for the 25th (0.6 percentage points p.a.) and the 75th percentiles (0.6 pp.) while for the 5th and 95th percentiles there were increases of 1.0 and 0.2 pp. respectively.

[7] In 2014, the average portfolio yield was 44% and the distribution of portfolio yield is thus skewed to the right. The average portfolio yield weighted by GLP was 24.8% and the average yield weighted by the number of borrowers 29.9%.

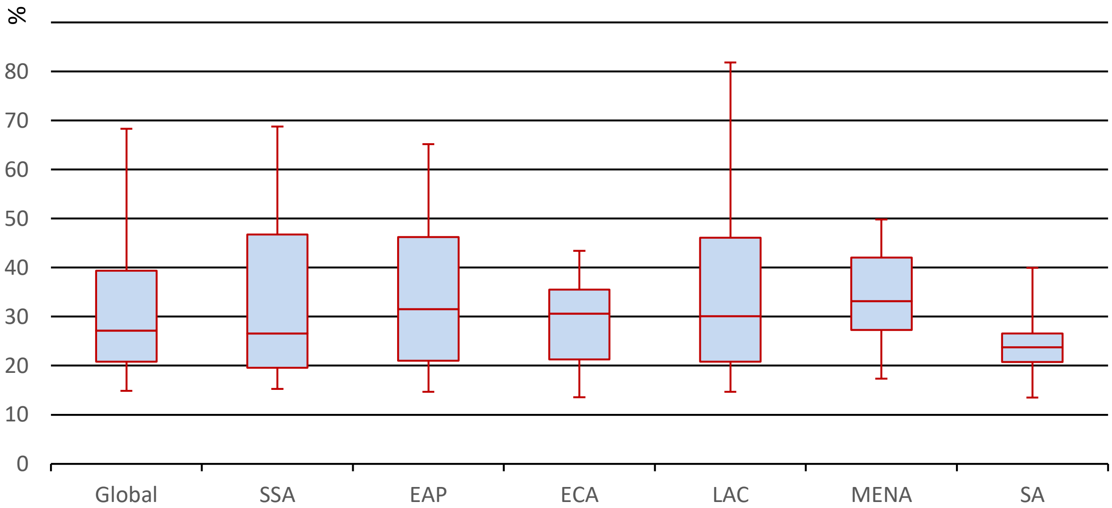
Figure 7: Portfolio Yield Distribution



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes 9,320 observations. The upper (lower) end of each box represents the 75th (25th) percentile. The horizontal line within the box is the median. Upper and lower error bars represent the 95th and 5th percentiles, respectively.

Regions. Wide variations can be observed between the regions (Figure 8). MFIs in South Asia usually do not charge more than 20.7% to 26.5% annually while the middle 50% of Latin American MFIs demand between 20.8% to 46.1% p.a. While 5% of MFIs from EAP charge 14.7% and less, one in twenty MFIs from LAC charges more than 81.8%. The widest range of reported portfolio yields can be found in LAC and SSA, the lowest in South Asia.

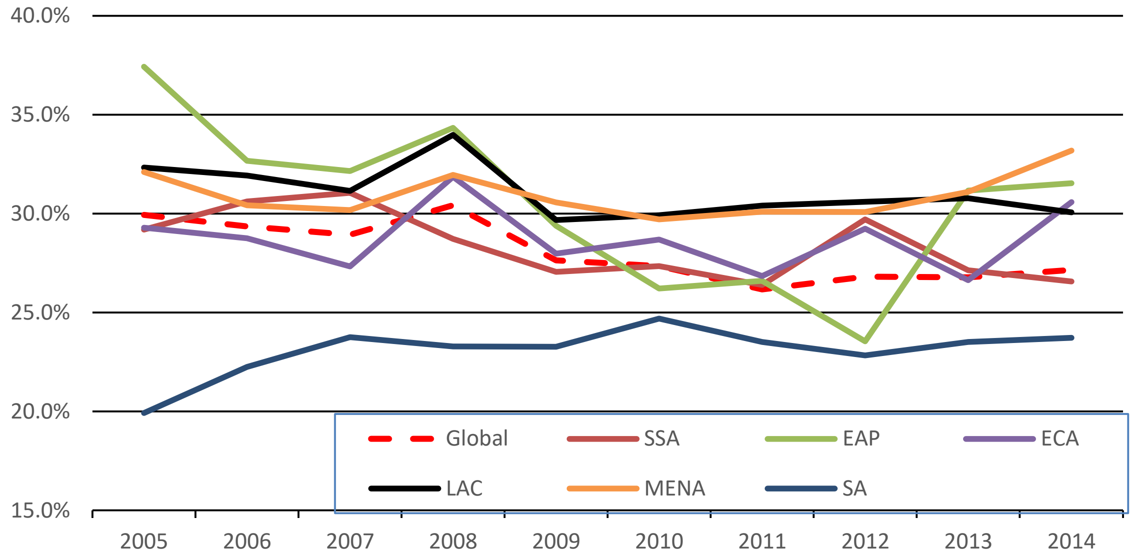
Figure 8: Portfolio Yield by Region (2014)



Source: Author's rendering of MixMarket data (2014).
Note: Includes 866 observations. The upper (lower) end of each box represents the 75th (25th) percentile. The horizontal line within the box is the median. Upper and lower error bars represent the 95th and 5th percentiles, respectively.

The development of interest rates has been uneven between the regions. Figure 9 shows the median reported portfolio yield by region and year. The overall downward trend was most pronounced in the still underdeveloped microfinance markets of EAP with the median portfolio yield declining from 37.4% to 31.5% (-1.7 pp. p.a.) followed by SSA (-0.9 pp.) and LAC (-0.7 pp.). On the contrary, the SA yields increased annually by 1.7 pp., followed by ECA (0.4 pp) and MENA (0.3 pp.).

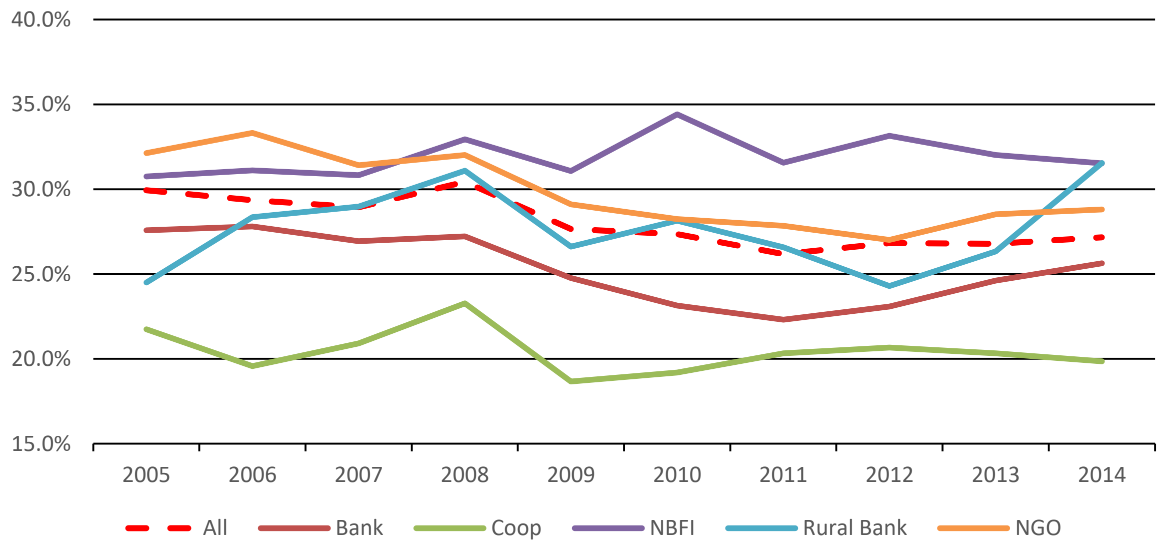
Figure 9: Median Portfolio Yield by Region



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes 9,320 observations.

Legal Status. Turning from the regions to the legal form of MFIs, Figure 10 shows that today NBFIs and rural banks charge the highest interest rates, followed by NGOs, banks, and cooperatives. The largest reductions of portfolio yields can be attributed to NGOs (-1.1 pp.), cooperatives (-0.9 pp.), and banks (-0.8 pp. p.a.), while rural banks and NBFIs increased their interest rates (2.5 pp. and 0.3 pp. respectively).

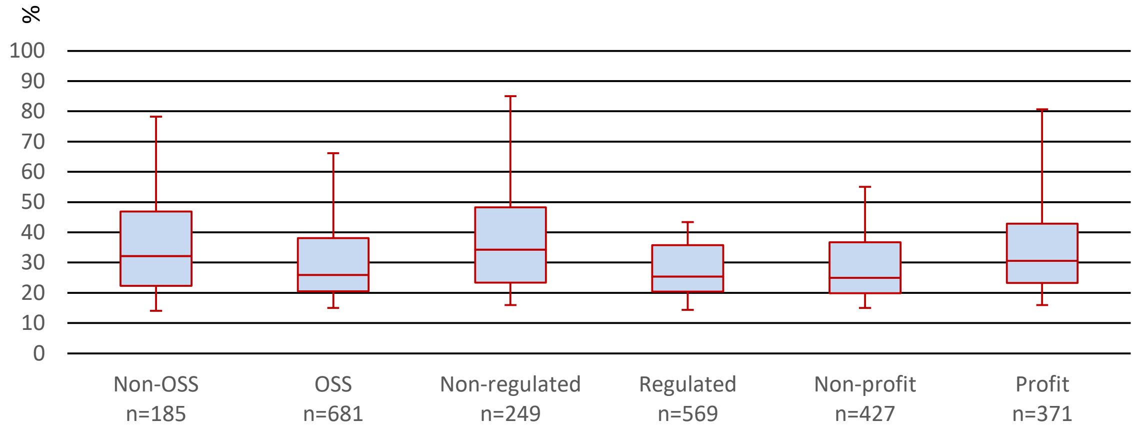
Figure 10: Median Portfolio Yield by Legal Status



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes 9,320 observations.

Other characteristics. One would suspect that –ceteris paribus- an MFI charging higher interest rates would be more likely to be profitable. However, as Figure 11 shows, *operationally self-sufficient* MFIs reported lower values for the median portfolio yield as well as lower 95th and 75th percentiles for 2014. The difference between the 5th and 95th percentile is much higher for Non-OSS than for OSS MFIs.

Figure 11: Portfolio Yield by Institutional Characteristics (2014)



Source: Author's rendering of MixMarket data (2014).
Note: Includes 866 observations. The upper (lower) end of each box represents the 75th (25th) percentile. The horizontal line within the box is the median. Upper and lower error bars represent the 95th and 5th percentiles, respectively.

In 2014, *regulated* MFIs reported lower yields than non-regulated MFIs (Figure 11). Over the entire time span from 2005 to 2014, the median portfolio yield from regulated MFIs was below the median portfolio yield of unregulated ones. The difference increased from 1.5 pp. in 2005 to 8.4 pp. in 2014, peaking in 2013 with 9.4 pp. Non-regulated MFIs are mainly NGOs (66.3% in 2014) and NBFIs (26.1%) and they tend to give out smaller loans than regulated MFIs. On the other hand, 43.1% of the regulated MFIs are NBFIs while banks, cooperatives, and NGOs made up 16.2 to 21.6% of this category each. The lower interest rate levels of regulated MFIs might be due to pressure for price transparency by the regulator, interest rate ceilings or adverse selection, as explored in the literature review. In addition, the higher loan sizes are likely to play an important role.

The last characteristic explored in Figure 11 is the *profit status* of the MFIs. In 2014, non-profit MFIs were mainly NGOs (58.5%), cooperatives and credit unions (28.3%), and NBFIs (10.5%). For-profit institutions were mainly NBFIs (70.0%), banks (22.1%), and rural banks (2.2%) are included in the dataset. All explored percentiles are higher for for-profit institutions, with the median at 25.0% for non-profits vs. 30.6% for for-profit MFIs. Non-profit institutions managed to lower their interest rates from 2005 to 2014 by 4.9 pp. while their for-profit peers raised them by 0.7 pp. in the same timeframe. This feat is even more noteworthy, given that non-profits hand out smaller loans: The median for-profit MFI had an average loan size of 33.9% of GNI p.c., the corresponding figure for non-profits was 22.8%. For-profit orientation is common in ECA and SA while MFIs in MENA, LAC, EAP, and SSA are predominantly non-profits.

A common hypothesis is that small loans incur high operational costs relative to their amount and thus require the MFI to charge high interest rates. Descriptive evidence supports this assumption. MixMarket clusters MFIs according to their average loan size as percentage of GNI p.c. in low end (<20% or <USD150), broad (20 – 149%), high end (150 – 250%), and small business (>250%). Figure 12 demonstrates that small loans have indeed to be repaid with a higher interest rate. The only disparity from the expected concerns the higher loan sizes, were the small business cluster reports for some years a higher median portfolio yield than the high end cluster. While the low end and high end cluster increased interest rates from 2005 to 2014, the broad and small business cluster lowered interest rates. All clusters remained fairly stable over the timeframe, with the broad segment (which also happens to be the largest cluster) experiencing the largest change (1.6%).

Figure 12: Median Portfolio Yield by Target Market

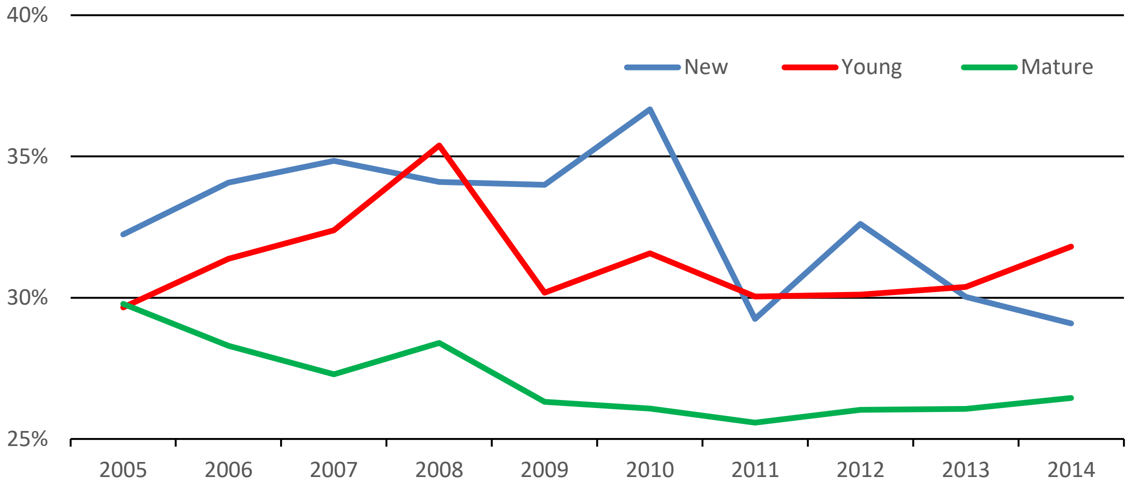
Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes 9,320 observations.

Descriptive analysis also supports the hypothesis that MFIs can reduce their interest rates with *age,* due to learning curve effects. Figure 13 shows mature MFIs (older than eight years) reporting a median yield of 26.5% in 2014 while new ones (up to four years) report 29.2% and young ones even 31.8%.[8] However, the figure illustrates that young (five to eight years old) and mature MFIs almost reported the same level of interest rates in 2005 and developed in opposite directions from there. New MFIs charged higher interest rates in 2005 and took a similar development as mature MIs by dropping rates from 2005 to 2014 by 3.2%. Several reasons can be found for the lack of disparity between the age categories. For example, the difference in scale was not yet so pronounced between mature and newer MFIs in 2005, when the global microfinance sector was less developed. In addition, many MFIs in this period were built from scratch according to international best practices. This applies e.g. to the ProCredit banks and the Finca and ProMujer affiliates. An additional factor is that in these pioneer years, MFIs were built in the most favorable market environments. As competition in these markets

[8] Transition of an MFI from one age category (e.g. New) to another (e.g. Young) from one reporting period to the next is possible.

increased and saturation set in, new greenfield branches were created increasingly in more difficult countries and environments, making higher interest rates presumably a necessity.

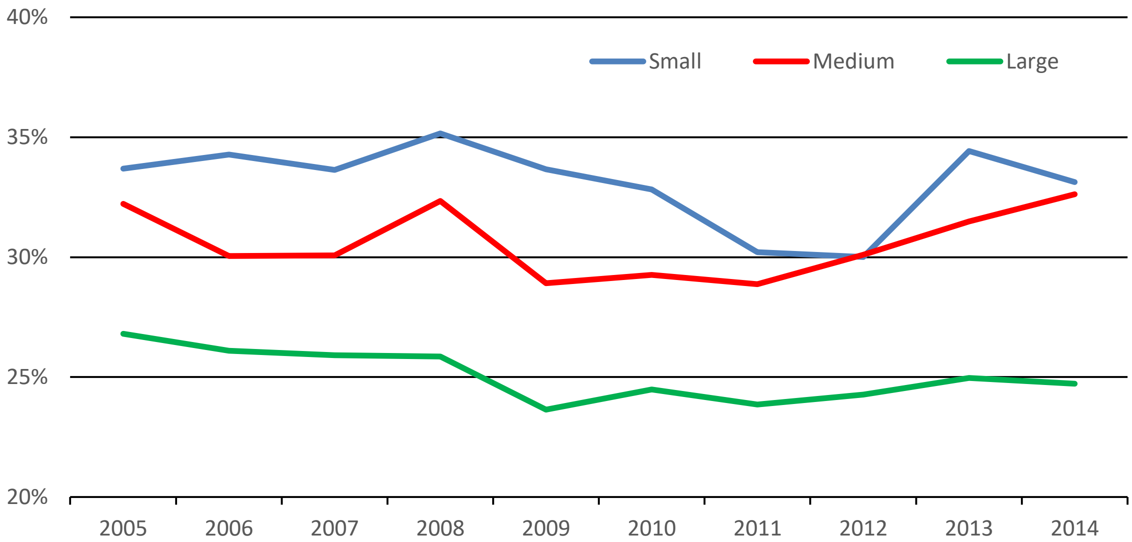
Figure 13: Median Portfolio Yield by Age



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes 9,320 observations. New MFIs 0-4 years, young 5-8 years and mature >8 years old.

Aside from learning curve effects, scale effects could lead to efficiency gains. Clustering the MFIs into small (<10,000 borrowers), medium (between 10,000 and 30,000), and large institutions (>30,000), it becomes apparent that the latter category consistently reported the lowest median portfolio yield (Figure 14). In 2014, however, hardly any differences between small and medium institutions can be noted.

Figure 14: Median Portfolio Yield by Scale



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes 9,320 observations.

3.2.3. Cost Channels

Interest rates are charged to cover the costs a MFI incurs. These are predominately personnel, administrative, funding and provisioning expenses. Other costs can be e.g. commissions or taxes. All these costs have to be covered by income, which in the case of MFIs is mostly financial income (interest and fees). All income, which has not been spent on the costs, can be retained as a profit. This gives us the following formula (adapted from Rosenberg et al. 2013):

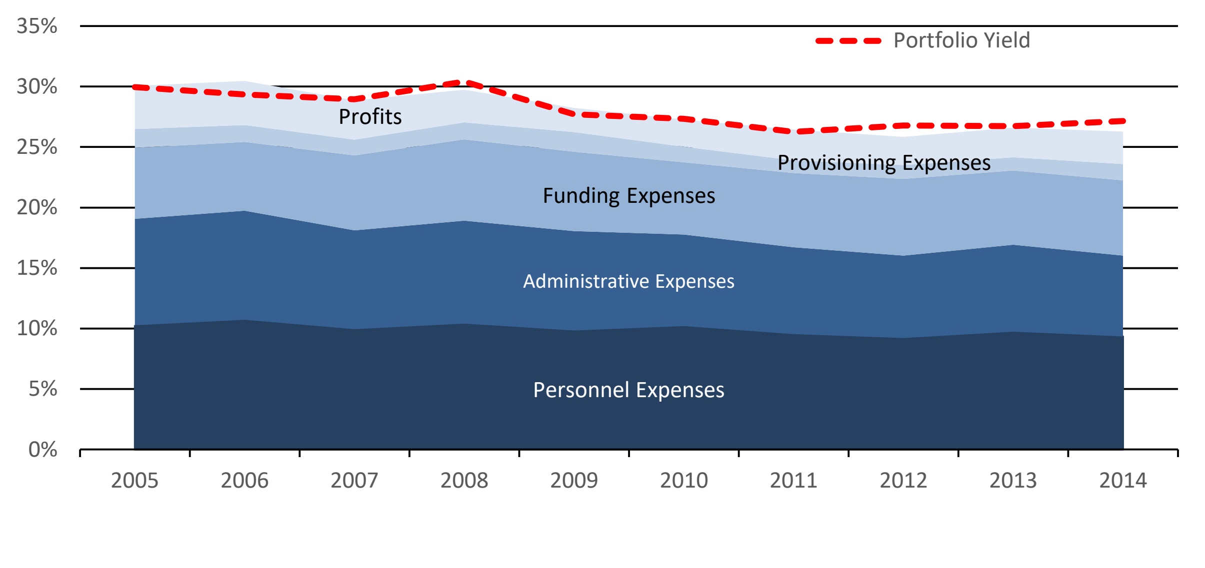
1) $income\ from\ loans + other\ income = personnel\ expenses + administrative\ expenses + funding\ expenses + loan\ loss\ provsion\ expenses + other\ expenses + taxes + profit$

MixMarket provides information for each of these items except for other income, other expenses and taxes. For lack of an alternative, these items are hence ignored in the subsequent analysis. Due to the lack of data on other income, other expenses and taxes, I approximate income from loans withe the five expense categories mentioned above.

Figure 15 shows the development of cost channels, profits and portfolio yield in the years 2005 to 2014 (all scaled to GLP)[9]. While the decline in interest rates is familiar from section 3.2.2, the figure allows an insight on how MFIs were able to reduce their interest rates. The figure also visualizes that portfolio yield indeed approximately amounts to the sum of costs and profit, in some years being slightly higher or lower. This might be explained by methodological issues[10] , errors in the data set or due to the influence of other income, other expenses and taxes. As seen in the graph, the reduction of portfolio yield from 2005 to 2014 of 2.8 p.p. is even exceeded by the overall reduction of costs and profit of 3.8 p.p. in the same period.

[9] Example: The 9.4% value for personnel expenses in 2014 means that during 2014 the median MFI incurred personnel expenses which amounted to 9.4% of the MFI's average GLP during 2014.
[10] For each of the cost items, the portfolio yield, and the profit, the median value of all observations is taken. This method helps against outliers, which can influence the average value. However, due to the distinctive distributions of the five variables it is unlikely that there is a 100% match between the median portfolio yield and the sum of the median components.

Figure 15: Cost Channels, Profits and Portfolio Yield



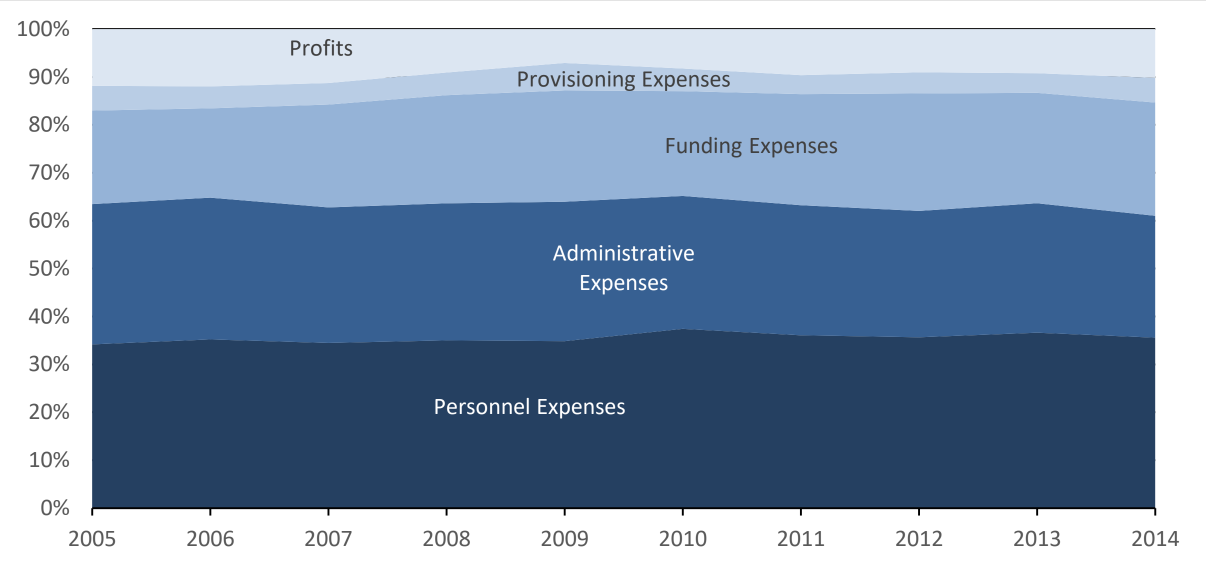
Source: Author's rendering of MixMarket data (2005-2014).

Note: Includes 9,290 observations (30 observations were excluded from the full data set due to missing data). Each of the five components' value is the median from its respective distribution. All five components are scaled to GLP.

Figure 16 uses the same data as Figure 15 but scales the analyzed components of portfolio yield to 100% to allow for a better comparison. As evident from both figures, *personnel expenses* make up the biggest part of costs. In 2005, annual personnel expenses corresponded to 10.3% of the GLP; in 2014, this figure was down to 9.4% (a drop of 0.9%). However, despite the relative reduction to GLP their relative share on all costs and profit has increased from 34.2% in 2005 to 35.6% in 2014 (plus 1.4%). The second largest component is *administrative expenses*, which show the biggest decline of all components from 8.8% to 6.7% of GLP, a drop of 2.1%. This is mirrored in arelative drop from 29.3% to 25.4% of total costs and profit, a drop of 3.9%. *Funding costs* for MFIs were 5.9% of GLP in 2005, peaked during the financial crisis in 2008 at 6.7% and cut back since then to 6.2% in 2014. . While interest rate levels in the developed world have plummeted since the financial crisis, the higher level of funding costs for MFIs could be explained by an increase in leverage[11]. Another factor might be the limited availability of subsidized funding, which more and more MFIs compete for. The development of funding costs is reflected in an increase from 19.5% to 23.6% of total costs and profit. One of the great successes of microfinance has been the ability to ensure repayment of the loans. MFIs around the world have been able to maintain good portfolio qualities with different technologies and mechanisms (Armendáriz & Morduch 2010). There have been crises in specific microfinance markets (Chen et al. 2010), but overall MFIs have shown a certain resilience to macroeconomic shocks, as detailed in the literature review. For this reason, *provisioning expenses* are only a minor cost factor for MFIs, with an average over the years of just 1.3% of GLP. In the global crisis year of 2009, the median provisioning costs peaked at 1.6%, hit a new low in 2011 at 1.0% of GLP and since then increased slightly to 1.4% of GLP and 5.1% of all interest rate components in 2014.

[11] The median debt to equity ratio increased from 2.6 to 3.2 during the years.

Figure 16: Cost Channels and Profits (scaled to 100%)



Source: Author's rendering of MixMarket data (2005-2014).
Note: Includes 9,290 observations (30 observations were excluded from the full data set due to missing data). Each of the five components' value is the median from its respective distribution. All five components are scaled to 100%.

In the past years, MFIs reduced their interest rates (-2.8%) slightly less than they reduced all costs (-2.9%). As outlined above, personnel and administrative expenses were the drivers of the cost reductions. Funding costs have increased only slightly, while the low level of provisioning costs limits its potential for cost saving measures. The analysis shows that cost reductions were handed on by MFIs to the borrowers via lower interest rates. The decline of profits from 3.6% of GLP in 2005 to 2.7% in 2014 (minus 0.9%) fosters the assumption that MFIs had to lower interest rates and could not keep them up to maintain the same level of profits.

3.3. Hypotheses

Taking the discussed literature and the presented data set evidence together leads to the hypothesis that personnel expenses are a big driver of MFI interest rates. Therefore, the main hypothesis to test is:

H1: There is an economically and statistically highly significant positive relationship between personnel expenses of MFIs and the portfolio yield charged by MFIs.

Second, the relationship of MFI interest rates and average salaries paid by MFIs is analyzed. This step aims at providing a starting point, where future research on MFI interest rates could focus on within the personnel expenses. Thus, the third and last hypothesis to test is

H2: *There is a highly economic and statistically significant positive relationship between average salaries paid by MFIs and portfolio yield charged by MFIs.*

4. Empirical Methodology

Section 4 presents the econometric method and the variables used to test the previously presented hypotheses.

4.1. Econometric Method

Subsection 4.1.1 outlines the motivation for the chosen two-way fixed-effects approach and discusses alternatives. Subsection 4.1.2 presents the actual estimation strategy. Limitations of the chosen strategy are discussed in section 5.3.

4.1.1. Choice of Econometric Approach

The data set used is an unbalanced panel with a large number of observations and a small number of time periods. A fixed-effects (FE) approach is chosen to both assess the cross-sectional and the time-series dimension of the panel and to deal with its unbalanced nature (which made a First-Differences approach unfeasible). More specifically, a two-way fixed-effects (FE) approach is used to consider time-specific and individual-specific fixed effects. Two-way means that fixed-effects are clustered at entity level (MFI) and time level (year).

FE are used if the researcher is only interested in the impact of variables that vary over time. FE inspect the relationship between independent and dependent variables within an entity (country, institution, person, etc.). Each entity has its own individual characteristics, which may or may not influence the independent and dependent variables (for example, the regulation status of a MFI could influence interest rate levels due to interest rate ceilings imposed by the government of a country). When using FE it is assumed that some characteristic within the individual may affect or bias the independent or dependent variables. This characteristic needs to be controlled for. This is the logic behind the assumption of the correlation between the entity's error term and the independent variables. Employing FE removes the effect of those time-invariant characteristics, thus the net effect of the predictors on the outcome variable can be assessed. In addition, the FE model assumes that those time-invariant characteristics are unique to the individual and are not correlated with other individual characteristics. Because each entity is different the error term of the entity and the constant (that captures individual characteristics) may not be correlated with other error terms. If the error terms would be correlated, then FE would not be feasible since inferences may not be correct (Torres-Reyna, 2007, Woolridge, 2006).

An important advantage of the two-ways FE-model is that with the removal of time invariant variables all invariant, unobserved individual effects are entirely removed. A simple example for such an invariant, unobserved individual effect could be regulation status of a MFI, if it does not change over time. Another example could be cultural aspects of the environment a MFI operates in, which can be assumed to stay constant over the period of observation. Both factors could have influence on the interest rate charged by the MFI but are removed in the two-way FE approach. Therefore, the probability of containing omitted variable bias is decreased. A drawback is the loss of one degree of freedom for each MFI, which does not have an influence on estimation results due to the large amount of observations.[12] The “robust standard errors” option in Stata is used to control for heteroscedasticity. In a fixed effects estimator the robust method automatically clusters standard errors by the specified ID (Stock & Watson, 2008). This is tested by clustering standard errors by MFI, results are the same as with robust standard errors. Since the cluster method additionally controls for serial correlation, this is accounted for in the estimation strategy. Limitations of the chosen approach will be discussed in section 5.3.

An alternative way of dealing with unbalanced panel data would be applying a random-effects model. Thus, a Hausman test (with and without time dummies) is applied to test the necessary assumption that the (unobserved) individual specific effects are random values from a given distribution and that they are uncorrelated to all explanatory variables (tables 9-10 in the appendix). In this case, the test rejects the null hypothesis and it is therefore assumed that there are systematic differences between the coefficient estimates in FE and random-effects models. This result is in line with expectations, since it is very hard to justify the assumption of no correlation between the many controls and unobserved individual specific effects. Thus, no random-effects approach is applied. The chosen method is consistent with existing empirical research using MixMarket data (e.g. Gonzalez 2007b; Assefa et al. 2013; Cotler & Almazan 2013).

The regressions include time dummy variables to capture the influence of aggregate (time-series) trends. This leads to a further loss of degrees of freedom and thus adds imprecision to the parameter estimates. Ignoring time effects seems however not to be a proper measure: a Wald test applied on the baseline regressions suggests that the time dummies are jointly significant (table 10 in the appendix).

4.1.2. Estimation Strategy

Three regressions are employed to test the two hypotheses introduced in 3.3.

The first baseline model regresses *portfolio yield* on *personnel expenses*. The baseline model is extended in additional regressions with control variables of costs channels, MFI-specific variables and exogenous controls to check robustness. This leads to the (simplified) equation:

$$2)\ Yield_{it} = \beta_0 + \beta_1 Persex_{it} + \beta_2(Costs_{it}) + \beta_3(MFI - specific_{it}) + \beta_4(Exogenous_{it}) + Year_t + a_i + u_{it}$$

where $Yield_{it}$ represents the dependent variable portfolio yield for MFI i in time period t. β_0 is the constant. $\beta_1 Persex_{it}$ is the main term of interest with personnel expenses as independent variable and β_1 the coefficient of interest. $\beta_2(Costs_{it})$, $\beta_3(MFI - specific_{it})$ and $\beta_4(Exogenous_{it})$ represent the (simplified) inclusion of the control variables. In a lengthy version of the formula and congruent with the regressions each control variable would have its own coefficient. $Year_t$ represents the set of time dummy variables included to account for the fixed time effects. a_i is the time-invariant error component and u_{it} the error term.

[12] Since a within estimation can only be done with at least two observations per entity, MFIs reporting only once are not considered in the FE regressions.

To confirm the assumed and by high correlation obvious relationship between personnel expenses and average salaries, a regression of personnel expenses on average salaries was performed (see appendix pp. 51-52). Results affirm average salaries to be the main driver of personnel expenses.

Next, to test *H2*, *portfolio yield* is regressed on *average salaries*. The baseline model is enhanced with MFI-specific and exogenous control variables. This leads to the (simplified) equation:

$$3)\ Yield_{it} = \beta_0 + \beta_1 Wage_{it} + \beta_2 (MFI - specific_{it}) + \beta_3 (Exogenous_{it}) + Year_t + a_i + u_{it}$$

where $Yield_{it}$ represents the dependent variable portfolio yield for MFI i in time period t. $\beta_1 Wage_{it}$ is the main term of interest with average salaries as independent variable and β_1 the coefficient of interest. The same MFI-specific and exogenous control variables as in equation (2) are included together with the familiar time dummies and error terms.

4.2. Variables

This subsection presents the variables used in the empirical analysis and links them to the hypotheses developed at the end of the last section. A list of all variables, their respective abbreviation used in the regression analysis, a description of the variable, and the source can be found in the appendix (Table 5). Descriptive statistics for each variable are also included in the appendix (Table 6-7).

4.2.1. Dependent Variables

This thesis seeks to find the main determinant(s) of microcredit interest rates. As virtually all research on this topic, the proxy used in this thesis for the interest rate is portfolio yield (named Yield in the regressions). Portfolio yield is calculated as follows:

$$4)\ Portfolio\ Yield = \frac{Interest\ and\ Fees\ on\ Loan\ Portfolio}{Loan\ Portfolio, gross, average}$$

As described in equation (4), portfolio yield includes all financial income (basically interest income and fees). It is expressed as a percentage of the MFI's gross loan portfolio. A decrease in portfolio yield can be due to a variety of factors. It can occur if the MFI lowers its interest rates on one or more products, if disbursement fees are lowered, if clients shift from expensive short-term loans to cheaper loan products. A decrease of yield can also occur if portfolio quality worsens: non-performing loans are included in GLP but do not generate interest revenue. Therefore, portfolio yield is not equal to the actual interest rates charged and is thus an imperfect proxy for the purposes of this thesis. The annual percentage rates (APR) or effective interest rates on the many loan products of MFIs might be better in expressing the real costs a borrower has to bear, however data availability is significantly lower[13] and compilation would pose major difficulties. Comparisons between the portfolio yields reported to MixMarket and the APR information collected by MFTransparency suggests that portfolio yield underestimates the costs to borrowers by 5 to 6 percentage points (Gaul 2011; Rosenberg et al. 2013; Roodman 2012). Yet, there is a strong correlation between yield and APR (Gaul 2011) and thus it is reasonable to assume that the main results obtained by analyzing yields can be transferred to APRs.

[13] MFTransparency (www.mftransparency.org) is collecting information on APRs but has so far collected information only on a few countries. Missing is also time series data.

4.2.2. Independent Variables

Personnel expenses (Persex) serves as independent variable in the first estimation (see equation (2) in 4.1.2). They are calculated as follows:

$$5)\ Personnel\ Expenses = \frac{All\ personnel\ expenses\ related\ to\ operations}{Loan\ Portfolio, gross, average}$$

As described in equation (5), personnel expenses include all personnel expenses related to operations (wages, benefits, trainings and payroll taxes). Using the same approach as with portfolio yield before, personnel expenses are divided by the gross loan portfolio and expressed as a percentage.

As second independent variable *Wage* is introduced for the second estimation (equation (3) in section 4.1.2) It is calculated as follows:

$$6)\ Wage = \frac{Average\ salary\ per\ staff\ member}{GNI\ p.c.}$$

Wage sets the average salary paid by an MFI into relation to the gross national income (GNI) per capita (p.c.) of the country. This variable disposes the monetary terms and allows thinking in relative terms instead. Now it is possible to compare wage levels paid by MFIs in different countries and regions and analyze their effect on personnel expenses and interest rates. In their microeconomic analysis of market power of MFIs, Mersland & Strøm (2011) use the indicator (without GNI p.c. adjustment) and find (as a byproduct) and finds positive effects on the portfolio yield.

4.2.3. Control Variables

Potential influencing factors of portfolio yield and personnel expenses are included as control variables in the regressions. The chosen control variables include both institution-specific factors as well as exogenous factors. As will be discussed in more detail in the subsection 4.2, the econometric approach chosen in this study is a two-way fixed effects model. Thus, only factors that vary over time are included as control variables in the analyses.

Institution-specific Control Variables

Financial expenses (Finex), provisional expenses (Provex) and administrative expenses (Admex), all scaled to GLP, are included as control variables in the regression. They represent the various cost channels through which portfolio yield may be affected.

Return on GLP (ROGLP)[14] controls for profits. The earlier introduced Operating Self-Sufficiency (OSS) serves as profitability indicator. The Debt-Equity Ratio (Leverage)[15] controls for the degree a MFI is accessing external funding. The ratio of GLP to total assets (GLPTO) captures how much of its assets the MFI uses for productive purposes. All four indicators serve as controls for the underlying business model of an MFI, its risk behavior and profitability.

[14] The ratio is obtained by setting the net income into relation with the total gross loan portfolio of an institution.
[15] The ratio is obtained by dividing the sum of deposits and borrowings of an MFI by its equity.

Due to lack of data, the exact age of each MFI is not included, but a classification into three age groups: New MFIs have been operational since less than five years, young MFIs for up to eight years, and mature MFIs have a track record of more than eight years. Those three categories are captured by the dummy variables AgeNew and AgeYoung.

Five variables are included to control for the client structure of MFIs: the total number of borrowers expressed as logarithm (LogBorr) the ratio of female borrowers to total borrowers (FemBorr), the ratio of borrowers to loan officers (BorrLoanOff), the ratio of borrowers to total staff (BorrStaff) and the average loan size per borrower (LoanBalBorr).

Exogenous Control Variables

Seven variables are included to control for (macroeconomic) country specific factors that are assumed to be related to interest rates of MFIs. The GNI p.c. (LogGNIpc), and the population size of a country (LogPop), both expressed as logarithm, control for the "status" of a country. The growth rate of GNI p.c. (GNIpcGr) and the inflation rate (Infl) adjust for the current economic performance of the country where the MFIs operate in. Population density (PopDens) , measured as people per sq. km of land area, is included as an often cited influence on MFIs efficiency. The development of the entire financial sector (DomCr) is accounted for with the amount of domestic credit to private sector participants as a percentage of GDP. Last, competition (Comp) in the microfinance market is considered with a proxy, namely the number of all microcredit borrowers in a country as a share of the country's total adult population.

Time Dummy Variables

Time dummy variables for each year are included to capture year specific effects with 2005 as the excluded period. This may be especially relevant to control for the financial market dynamics around the 2008 financial crisis and the overall downward trend of global interest rates.

5. Empirical Results

This section presents the results of the regressions, which were run according to the methodology presented in the previous section. Significance levels with p-values below one, five, and ten percent are labeled accordingly. The dependent, independent and control variables are chosen because of theoretical considerations outlined in section 2 and the descriptive analysis in section 3. Thus, not all control variables show statistical significance but were considered important to include in the extended versions of the regressions. This section focuses on looking at the econometric results and interpreting them in its economic context. The limitations discussed in section 5.3 have to be kept in mind when interpreting the results.

5.1. Personnel Expenses as Determinant of Portfolio Yield

The results of the regression of portfolio yield on personnel expenses are presented in table 3. As outlined in section 4.1.2, the baseline regression (1) is complemented with various control variables (2)-(6).

In the baseline regression (1), personnel expenses (scaled to GLP) show a highly statistically significant positive relationship with portfolio yield (also scaled to GLP). The coefficient, introduced as β_1 in section 4.1.2, shows that with an increase of personnel expenses (scaled to GLP) by one percentage point, portfolio yield (as well expressed as ratio to GLP) increases by 0.509 percentage points, roughly half a percent. The regression includes 2,009 MFIs with 9,056 observations. The R^2 of 99.4% shows that the linear model (in the baseline: personnel expenses) explains almost all variation in the dependent variable portfolio yield. The time dummy variables have in 2009, 2010 and 2012-2014 statistically significant negative coefficients, hinting at the predicted decline of portfolio yield over time.

The baseline regression is augmented by adding control variables. In regression (2), the remaining cost channels financial expenses, loan loss provisioning expenses and administrative expenses are added. None of them is statistically significant (p-value below 5%), which leaves β_1 almost unchanged. In regression (3), MIF-specific controls are added and the cost channels from (2) are removed. Although the total number of borrowers and the ratio of borrowers to loan officers prove highly statistically significant, β_1 shows the same value as in (1). When including both controls for cost-channels and MFI-specific factors in regression (4), the coefficient of interest changes to 0.32. Provisional expenses, ROGLP, the number of borrowers, ratio of female borrowers and ratio of borrowers to loan officers are statistically significant. Next, in (5) exogenous factors are added to the baseline. Inflation, population size and population density are statistically significant, nevertheless, β_1 remains the same as in (1). Last, all controls are added in (6), which leads to a coefficient of 0.321 while including 7,134 observations from 1,713 MFIs and explain with a R^2 99.7% of variation in portfolio yield.

The coefficient of interest, β_1, remains highly statistically significant in all regressions (1) to (6). Thus, the null-hypothesis for *H1* can be rejected at the 1% level. Personnel expenses are highly statistically significant and positive related to portfolio yield. The coefficients of the time dummy variables follow expectations of general interest rate decrease compared to the base year of 2005, with the largest coefficient (in absolute terms) in the last year of analysis 2014.

Table 3: Portfolio Yield Regression on Personnel Expenses

VARIABLES	(1) Baseline	(2) Costs	(3) MFI-specific	(4) Costs+MFI-specific	(5) Exogenous	(6) All
Persex	0.509***	0.516***	0.509***	0.320***	0.509***	0.321***
	(0.000788)	(0.00976)	(0.000684)	(0.0346)	(0.000776)	(0.0344)
Finex		0.00842		0.0714		0.0733
		(0.0775)		(0.166)		(0.170)
Provex		0.0708		0.379***		0.378***
		(0.0445)		(0.0520)		(0.0527)
Admex		-0.0751*		0.123		0.121
		(0.0391)		(0.0766)		(0.0761)
ROGLP			0.0133	0.210***		0.209***
			(0.0126)	(0.0297)		(0.0296)
Leverage			-8.16e-07	-3.01e-05		-2.72e-05
			(4.49e-05)	(3.13e-05)		(3.09e-05)
GLPTA			-0.00916	-0.0163		-0.0181*
			(0.00842)	(0.0106)		(0.0108)
OSS			0.0167	0.00838		0.00825
			(0.0124)	(0.00674)		(0.00674)
AgeNew			-0.0201*	-0.00482		-0.00399
			(0.0105)	(0.00886)		(0.00893)
AgeYoung			0.00262	0.000186		-0.000275
			(0.00571)	(0.00443)		(0.00454)
LogBorr			0.0683***	0.0320**		0.0344**
			(0.0230)	(0.0127)		(0.0134)
FemBorr			0.0266*	0.0365**		0.0314**
			(0.0147)	(0.0148)		(0.0151)
BorrLoanOff			-6.49e-07***	-5.21e-07***		-3.57e-07*
			(2.10e-07)	(1.93e-07)		(2.05e-07)
BorrStaff			-2.36e-05*	-2.72e-05		-3.17e-05
			(1.40e-05)	(2.14e-05)		(2.31e-05)
LoanBalBorr			0.00254	-0.000392		-5.72e-05
			(0.00189)	(0.00197)		(0.00198)
LogGNIpc					0.0762*	0.0568
					(0.0392)	(0.0346)
GNIpcGr					-1.91e-06	-5.68e-06
					(6.58e-06)	(4.66e-06)
Infl					-9.20e-06**	-6.86e-06*
					(4.37e-06)	(3.98e-06)
LogPop					0.388***	0.122
					(0.134)	(0.120)
PopDens					0.000489**	0.000300**
					(0.000194)	(0.000133)
Comp					-0.101	-0.223***
					(0.0615)	(0.0580)
DomCr					1.42e-05	1.39e-05
					(1.08e-05)	(9.49e-06)
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.269***	0.277***	-0.0140	0.135***	-2.951***	-0.998
	(0.00589)	(0.00677)	(0.0932)	(0.0481)	(1.009)	(0.906)
Observations	9,056	9,056	7,234	7,234	8,931	7,134
R-squared	0.994	0.994	0.996	0.997	0.994	0.997
Number of ID	2,009	2,009	1,725	1,725	1,998	1,713

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.2. Average Salaries as Determinant of Portfolio Yield

The results of the regression of portfolio yield on average salaries are presented in table 4. As outlined in section 3.4, the baseline regression (1) is complemented with various control variables (2)-(4). Please see table 12 in the appendix for a full regression table with all control variables.

Table 4: Portfolio Yield Regression on Average Salaries

VARIABLES	(1) Baseline	(2) MFI-specific	(3) Exogenous	(4) All
Wage	0.0243***	0.0248***	0.0243***	0.0248***
	(0.00598)	(0.00506)	(0.00598)	(0.00505)
Year controls	Yes	Yes	Yes	Yes
Constant	0.225***	1.355	-5.561***	-2.402
	(0.0358)	(0.867)	(1.909)	(4.153)
Observations	8,196	6,837	8,107	6,763
R-squared	0.822	0.846	0.822	0.846
Number of ID	1,876	1,648	1,863	1,636

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the baseline regression, average salaries show a highly statistically significant positive relationship with portfolio yield. The coefficient, introduced as β_1 in section 4.1.2, shows that with an increase of average salaries over GNI p.c. (both measured in USD) by one unit, portfolio yield (expressed as a ratio to GLP) increases by 0.0243 units (or 2.43 percentage points). Since, as pointed out before, the average salaries vary so much between MFIs this potentially translates into large differences in portfolio yield. The baseline includes 8,196 observations from 1,876 MFIs and the R^2 shows that the model accounts for 82.2% of variation in the dependent variable. The included time dummies are only statistically significant in the year of 2007.

In regression (2), from the previous regression familiar MFI-specific controls are added to the baseline to see whether different characteristics of MFIs will change the variable of interest. The coefficient for average salaries increases marginally to 0.0248, with leverage being the only statistically significant included control. The R^2 increases slightly to 84.6%. The addition of the familiar exogenous control variables, all of them statistically insignificant, in (4) and (5) leaves the previous regression results unchanged.

Thus, the null-hypothesis for *H2* that average salaries paid by MFIs are not significantly related to portfolio yield charged by MFIs can be rejected at the 1%-level.

5.3. Limitations

Several limitations might influence the validity of the empirical results presented in this thesis.

As detailed in section 3.1, MixMarket *data* is imperfect. The data is self-reported by MFIs and is thus likely to contain data errors[16]. MFIs could have reason to report higher profits to attract more funding. Furthermore, reporting to MixMarket is voluntary and therefore *self-selection bias* is inherent to the data set. As mentioned above, the fact that virtually all major MFIs report to MixMarket gives a certain confidence that the observed institutions mirror the MFIs the typical microcredit client deals with. Still, it is important to note that the main messages from this thesis might apply rather to the major, commercial MFIs than to small, subsidy-dependent microfinance programs and therefore external validity is limited.

The unbalanced nature of the panel with a varying number of observations per year is taken into account with the choice of the econometric model and does not pose a methodological problem. Still, while looking at the results it has to be kept in mind that the reporting MFIs change every year. However, taking a balanced panel by only considering MFIs reporting over the full horizon would have decreased sample size and global representation of MFIs drastically.

The number of observations is sufficiently large; however, the time dimension is restricted to the years 2005 to 2014. Thus, the years where many countries had to deal with the global financial crisis and its repercussions are embedded at the center of the time frame. In spite of the use of time dummies, it is therefore possible that empirical results are influenced by the crisis. The transferability of the results to the future is thus questionable. Nevertheless, the global approach of the thesis, the inclusion of several years before and after the peak of the crisis and the assumed and indirectlyreconfirmed lower dependence of microfinance markets on global financial markets seem to dampen this consideration to some extent.

Presumably, the endogeneity bias with highest relevance to this thesis is *reverse causality*. The interest rate might also explain the personnel expenses: For example, if a MFI has to reduce interest rates due to competition effects or regulatory intervention, the MFI will try to bring down operating costs, including personnel costs, in order to remain profitable. The profitability measures ROGLP and OSS might influence the behavior of interest rates, but the explanation also works in reverse: The interest rate level influences directly the ROGLP and the OSS. High interest rates might also influence the repayment behavior of borrowers and thus the provisioning costs. On the other hand, funding availability and costs might differ for MFIs with very low or high operating expenses and MFIs charging very high or low interest rates.

As one can think of a potentially almost unlimited number of possible determinants of interest rates, it makes the study prone to *omitted variable bias*. However, the two-ways FE approach helps in reducing this bias: the same factors are omitted for each single MFI and in each observation. Assuming the omitted variable is fixed (e.g. cultural aspects or literacy rates should have little fluctuation from one year to the next), the variable will take on the same values each time we observe the same MFI. As described in section 4.1.1, these invariant individual effects are removed in the data transformation

[16] For example, the descriptive statistics in table 6 show that an MFI reported that 125.6% of its borrowers were women.

before the regression. Nevertheless, an omitted variable bias could remain due to possible interaction effects, which cannot be removed with the fixed-effects approach.

The limitation of data concerning the analyzed cost and income channels could influence results. The lack of data on other income, other expenses and taxes of MFIs is not assumed to have a systematic impact on the results, but cannot ruled out completely.

Measurement errors are expected since most of the data is obtained from MixMarket, which is, as mentioned above, self-reported. In addition, MFIs come from more than a hundred countries, of which many have their own accounting standards, e.g. the reported equity capital of one institution will have a different meaning from the capital reported by another institution. However, the measurement errors should be rather of random than of systematic nature: Given the law of large numbers, it is not expected that the measurement errors will significantly alter the results.

Aside of endogeneity, *multicollinearity* could be present in the set of explanatory variables. Correlations (reported in table 11 in the appendix) are in general rather low and therefore multicollinearity is not assumed to be a major issue.

Last, a few words shall discuss the location of this thesis within the context of microeconomic theory of *price*, *demand* and *supply*.
In this thesis, the offered good, the microloan, is assumed a homogenous good with one average price (portfolio yield as proxy for interest rate) per provider (MFI). In reality, almost uncountable variations of microloans exist, differing in disbursement, repayment, duration, collateral, covenants, grouping, etc. In addition, credit is a special good with characteristics of a service, where the "production" takes place in the presence of the customer. Data on interest rates charged for varying microcredit products is to the author's knowledge only available for single MFIs or MFI networks, but not in a global context.
The global demand for microcredit products remains unknown and to the author's knowledge, only rudimentary guesses exist. As described in section 2.2.3, microfinance still operates in mostly financially underdeveloped markets. It could therefore be assumed that a rather abundant and steady demand for microloans prevails. In the regressions, the control variable *DomCr*, which measures domestic credit to private sector as percentage of GDP, accounts for the level of development of a financial market.
As outlined in section 2.2.2 and in line with general price theory, several studies identified that too high interest rates could lead to reduced customer demand. In addition, price elasticity seems to depend on the wealth level of borrowers. Economic theory suggests that, all other factors equal, increased demand for microloans should lead to increased prices (interest rates). However, in this thesis, interest rates for microcredit products have fallen during the years.
As described in section 3.2.1, the number of MFIs has increased over the years, hinting at increased supply of microcredit products. To the author's knowledge, no studies on aggregate global supply of microcredit products exist. Theory would suggest that, all other factors equal, MFIs would choose to supply less microcredit in times of the observed falling interest rates.
Competition, as outlined in section 2.2.3, plays an important role in microfinance. In line with general economic theory, a downward pressure on interest rates can be expected. In the regressions, the control variable *Comp* (number of active microfinance borrowers / adult population) accounts for competition.

The quantity of outstanding microloans, stated as GLP in section 3.2.1, has increased manifold. This quantity has been cleared at market price. In well-functioning markets, it could be assumed that the observed outstanding quantity and price are close to equilibrium quantity and equilibrium price. Overall, the market experienced an expansion of microcredit quantity accompanied by decreasing prices.

6. Discussion and Concluding Remarks

The aim of this thesis is to gain insights into the level and development of the interest rates of MFIs and to identify the major determinants of these interest rates. As millions of poor borrowers rely on microcredit products to finance various aspects of their lives, the price of such products cannot be rated important enough. This study is based on earlier empirical and theoretical work that try to explain determinants of interest rates or studying related topics such as microfinance competition, efficiency and sustainability. Previous descriptive studies have identified operating expenses as the main cost channel, which influences MFI interest rates. This study contributes to the existing literature by shedding light on how personnel expenses are related to variations in interest rates. To capture the development of MFI interest rates after the commercialization of the sector and before, during and after the global financial crisis, a dataset from MixMarket containing 9,320 observations from 2,039 MFIs covering the years 2005 to 2014 is employed. The assessment of interest rates charged by such a large number of MFIs on global level over the long time span of 10 years has not been done previously in the literature and adds to national and regional studies of microfinance markets. Identifying personnel expenses as a major cost channel and average salaries (scaled to GNI p.c.) as a major MFI-specific factor while controlling for important MFI-specific and exogenous factors make this study unique.

In line with existing literature, reported annual median portfolio yield is used throughout the thesis as proxy for MFI interest rates. First, the data is analyzed in a descriptive way to give an encompassing overview of the level and development of interest rates. It studies the development of the major cost channels and clusters the data into different peer groups, some of them reappearing in the empirical analysis as control variables. Highlights from the analysis include the general decline of interest rates annually by 1.0 % with Latin American MFIs charging the highest and South Asian MFIs the lowest rates. The overall downward trend is most pronounced in East Asia and the Pacific region. NBFIs and rural banks charge the highest rates, banks and cooperatives the lowest. Sustainable, regulated and non-profit institutions charge lower rates than their peers. As expected, MFIs that are large, mature and targeted at rather well off customers or small businesses demand lower interest. The reduction of interest rates of 2.8% from 2005 to 2014 is exceeded by a reduction of costs and profits by 3.8%. The reduction of costs mainly stems from reductions in its two biggest components, personnel and administrative expenses. Profits also declined.

In the econometric analysis a two-way fixed effects approach with includes time dummy variables is chosen to deal with the cross-sectional and the time-series dimension of the unbalanced panel. Several institution-specific and exogenous factors, previously discussed in section 2, are included as control variables in order to isolate the underlying relationship. The analysis suggests that higher personnel expenses are associated with higher interest rates. This is consistent with the hypotheses. The estimate for the relationship between personnel expenses and interest rates is in all specifications positive and highly statistically significant. Findings from regression with MFI-specific and exogenous controls suggest that with an increase of personnel expenses by one percentage point, portfolio yield increases by 0.32 percentage points (both scaled to GLP). The suspected statistically highly significant positive relationship between personnel expenses and average salaries is confirmed. The second main regression shows that with an increase of average salaries by one unit, portfolio yield increases by 0.0248 units (measured as percentage points of GLP).

Despite the limitations to the results, which are discussed in section 5.3, one can draw some conclusions from the analysis, which are particularly important for managers of MFIs and policy makers of countries with a big microfinance sector. Interest rates and their development vary a lot between world regions and several institution specific characteristics such as age, legal status and for-profit orientation. Nevertheless, over the whole sample the general decline of interest rates came along with a decline in personnel expenses, administrative expenses and profits. From these potential channels, personnel expenses appear to be the cost channel, which mostly influences the variation of interest rates. Average salaries seem to be the MFI-specific factor that accounts for most variation in interest rates. The observed behavior is generally consistent with the hypotheses that higher personnel expenses and average salaries are associated with higher interest rates. Building on this, managers of MFIs might want to assess to what extent they can reduce their personnel expenses and look further into the wages paid to their employees. Furthermore, policy makers interested in the supply of affordable credit to the poorest of their population could focus on laying the foundations for MFIs to have sufficient access to qualified human capital. This might ultimately benefit borrowers and stakeholders.

Further research on determinants of microcredit interest rates, especially on personnel expenses and wages, is warranted as it might improve decisions by MFI-managers and policy makers and might ultimately benefit borrowers and stakeholders. Current evidence is limited and of varying quality. Since most empirical research has utilized a single data source (MixMarket), it would be worthwhile to perform such analyses with other data sources, such as the information pools of a major microfinance funder or a rating agency. Future research should investigate in depth the determinants of personnel costs, which are identified as the main cost drivers of MFIs. Differences in wage levels and its causes are of particularly high interest as brought forward by the analysis of this study. The availability of highly skilled human capital is another promising research area. Widely discussed are e.g. the potential benefits and efficiency gains of mobile banking and agent banking. However, these two technologies have still to prove their disruptive power when it comes to the provision of microloans (Hanouch & Rotman 2013). Research on this topic is likely to require the sourcing of new data.

Bibliography

Agarwal, N. (2006). Costing of MFIs. Microfinance Commercial Team, Rural Micro-banking & Agribusiness Group, ICICI Bank. Retrieved February 08, 2017, from http://www.spandanaindia.com/PDFs/CostingofMFIs_Nitin.pdf.

Ahlin, C., Lin, J. & Maio, M., (2011). Where does Microfinance flourish? Microfinance Institution Performance in Macroeconomic Context. *Journal of Development Economics*, 95(2), pp.105–120.

Armendáriz, B. & Morduch, J. (2010). *The Economics of microfinance* (2). Cambridge: MIT Press.

Assefa, E., Hermes, N., & Meesters, A. (2013). Competition and the Performance of Microfinance Institutions*. Applied Financial Economics*, 23(9), 767-782.

Bos, J.W.B. & Millone, M. (2012). Practice What You Preach: Microfinance Business Models and Operational Efficiency. Retrieved January 25, 2017, from http://umsbe.wufoo.com/cabinet/m7z8a3/HqcsfXWthWA%253D/bos__millone___microfinance_business_models_and_operational_efficiency.pdf.

Brand, M. & Gerschick, J. (2000). Maximizing Efficiency in Microfinance: The Path to Enhanced Ooutreach and Sustainability. Somerville, MA: ACCION International.

Campion, A., Ekka, R.K. & Wenner, M. (2010). Interest Rates and Implications for Microfinance in Latin America and the Caribbean. IDB Working Paper Series, 177. Washington, D.C.: Inter-American Development Bank.

CGAP (2010). Andhra Pradesh 2010: Global Implications of the Crisis in Indian Microfinance. *Focus Note 67*. Washington, D.C.: CGAP.

CGAP and Microfinance Information Exchange (2011). MIX Microfinance World: Sub-Saharan Africa Microfinance Analysis and Benchmarking Report 2010. Washington, D.C.: CGAP and Microfinance Information Exchange.

Chen, G., Rasmussen, S. & Reille, X. (2010). Growth and Vulnerabilities in Microfinance. Focus Note 61. Washington, D.C.: CGAP.

Chowdhury, A. (2009). Microfinance as a Poverty Reduction Tool—A Critical Assessment. United Nations, Department of Economic and Social Affairs (DESA) working paper (89*)*.

Conning, J. (1999). Outreach, Sustainability and Leverage in Monitored and Peer-monitored Lending. *Journal of Development Economics*, 60(1), pp.51–77.

Cotler, P. & Almazan, D. (2013). The Lending Interest Rates in the Microfinance Sector: Searching for its Determinants. *Journal of CENTRUM Cathedra*, 6(1), pp.69–81.

Cull, R., Demirgüç-Kunt, A. & Morduch, J. (2007). Financial Performance and Outreach: a Global Analysis of Leading Microbanks. *The Economic Journal*, 117, pp.107–133.

Cull, R., Demirgüç-Kunt, A. & Morduch, J. (2009a). Microfinance Meets the Market. *Journal of Economic Perspectives*, 23(1), pp.167–192.

Cull, R., Demirgüç-Kunt, A. & Morduch, J. (2009b). Banks and Microbanks. Policy Research Working Paper 5078. Washington D.C.: World Bank.

Cull, R., Demirgüç-Kunt, A. & Morduch, J. (2009c). Does Regulatory Supervision Curtail Microfinance Profitability and Outreach? Policy Research Working Paper 4748. Washington D.C.: World Bank.

Cull, R., Harten, S., Nishida, I. et al. (2015). Benchmarking the Financial Performance, Growth, and Outreach of Greenfield MFIs in Africa. *Emerging Markets Review*, 25, pp. 92-124.

D'Espallier, B., Hudon, M. & Szafarz, A. (2013). Unsubsidized Microfinance Institutions. *Economics Letters*, 120(2), pp.174–176.

D'Espallier, B, Goedecke, J., Hudon, M. et al. (2017). From NGOs to Banks: Does Institutional Transformation Alter the Business Model of Microfinance Institutions? *World Development*, 89, pp. 19–33.

Dehejia, R., Montgomery, H. & Morduch, J. (2012). Do interest rates matter? Credit Demand in the Dhaka Slums. *Journal of Development Economics*, 97, pp.437–449.

Demirgüç-Kunt, A., Beck, T. & Honohan, P. (2008). Finance for All? World Bank Policy Research Report. Washington, D.C.: World Bank.

Dougherty, C. (2007). *Introduction to Econometrics* 3rd ed., Oxford: Oxford University Press.

Fafchamps, M. & Pender, J. (1997). Precautionary Saving, Credit Constraints, and Irreversible Investment: Theory and Evidence from Serniarid India. *Journal of Business & Economic Statistics*, 15(2), pp.180–194.

Farrington, T. (2000). Efficiency in Microfinance Institutions. *MicroBanking Bulletin*, 4, pp.18–23.

Fernando, N.A. (2006). Understanding and Dealing with High Interest Rates on Microcredit: A Note to Policy Makers in the Asia and Pacific Region. Manila: Asian Development Bank.

Frank, C. (2008). Stemming the Tide of Mission Drift: Microfinance Transformations and the Double Bottom Line. Washington, D.C.: Women's World Banking.

Gaul, S. (2011). MFTransparency and MIX Market. *MicroBanking Bulletin*, April, pp. 1–5.

Global Impact Investing Network (GIIN) (2017). Personnel Expenses. Retrieved February 17, 2017, from https://iris.thegiin.org/metric/4.0/FP4831

Gonzalez, A. (2007a). Efficiency Drivers of Microfinance Institutions (MFIs): The Case of Operating Costs. *MicroBanking Bulletin*, 15, pp.37–42.

Gonzalez, A. (2007b). Resilience of Microfinance Institutions to National Macroeconomic Events: An Econometric Analysis of MFI Asset Quality. Mix Discussion Paper No. 1. Washington D.C.: Microfinance Information Exchange.

González, A. (2011). Defining responsible financial performance: understanding efficiency. MIX MicroBanking Bulletin.

Haq, M., Skully, M. & Pathan, S. (2009). Efficiency of Microfinance Institutions: A Data Envelopment Analysis. *Asia-Pacific Financial Markets*, 17(1), pp.63–97.

Helms, B. & Reille, X. (2004). Interest Rate Ceilings and Microfinance: The Story so far. Occasional Paper No. 9. Washington D.C.: CGAP.

Hermes, N., Lensink, R. & Meesters, A. (2009). Financial Development and the Efficiency of Microfinance Institutions. Centre for International Banking, Insurance and Finance Working Paper. Groningen: University of Groningen.

Hermes, N., Lensink, R. & Meesters, A. (2011). Outreach and Efficiency of Microfinance Institutions. *World Development*, 39(6), pp.938–948.

Hes, T., & Poledňáková, A. (2013). Correction of the Claim for Microfinance Market of 1.5 billion Clients. *International Letters of Social and Humanistic Sciences*, (02), 18-31.

Jansson, T. (2001). Microfinance: from village to Wall Street. Sustainable Development Department Best Practice Series. Washington, D.C.: Inter-American Development Bank.

Jia, X., Cull, R., Guo. P. et al. (2016). Commercialization and Mission Drift: Evidence from a Large Chinese Microfinance Institution. *China Economic Review,* 40, pp. 17–32.

Karlan, D.S. & Zinman, J. (2008). Credit Elasticities in Less-Developed Economies: Implications for Microfinance. *American Economic Review*, 98(3), pp.1040–1068.

Kennedy, P. (2003). *A Guide to Econometrics* 5th ed., Malden, MA: Blackwell Publishing.

Khalily, M. B., Khaleque, M. A., & Badruddoza, S. (2014). Impact of Regulation on the Cost Efficiency of Microfinance Institutions in Bangladesh. In Microfinance Institutions (pp. 139-161). Palgrave Macmillan UK.

León Castillo, J. & Jopen Sánchez, G. (2011). La Heterogeneidad del Microcrédito en el Sector Financiero Regulado Peruano. In J. León Castillo & J. M. Iguíñiz, eds. *Desigualdad Distributiva en el Perú: Dimensiones*. Lima: Fondo Editorial de la Pontificia Universidad Católica del Perú - PUCP, pp. 291–320.

McKim, A. & Hughart, M. (2005). Staff Incentive Schemes in Practice: Findings from a Global Survey of Microfinance Institutions. Washington D.C.: Microfinance Network & CGAP.

Mersland, R. & Strøm, R.Ø. (2008). Performance and Trade-offs in Microfinance Organizations—Does Ownership Matter? *Journal of International Development*, 20, pp.598–612.

Mersland, R. (2009). The Cost of Ownership in Microfinance Organizations. *World Development*, 37(2), pp.469–478.

Mersland, R. & Strøm, R.Ø. (2010). Microfinance Mission Drift? *World Development*, 38(1), pp.28–36.

Mersland, R. & Strøm, R.Ø. (2011). What Drives the Microfinance Lending Rate? Retrieved January 28, 2017, from http://www.rug.nl/research/globalisation-studies-groningen/research/conferencesandseminars/conferences/eumicrofinconf2011/papers/10a.oysteinstrom-mersland.pdf

Microfinance Information Exchange (MIX) (2011). MIX 2010 Benchmarks. Washington, D.C.: Microfinance Information Exchange.

Microfinance Information Exchange (MIX) (2012). 2012 Latin America & the Caribbean: Regional Snapshot. Washington, D.C.: Microfinance Information Exchange.

Morduch, J. (2000). The Microfinance Schism. *World Development*, 28(4), pp.617–629.

Morduch, J. (2013). How microfinance really works. *Milken Institute Review Second Quarter*, 51-59.

Nwachukwu, J., Asongu, S. (2015). The Determinants of Interest Rates in Microbanks: Age and Scale. *African Governance and Development Institute Working Paper*. WP/15/004.

Patten, R.H., Rosengard, J.K. & Johnston, J.D.E. (2001). Microfinance Success amidst Macroeconomic Failure: The Experience of Bank Rakyat Indonesia during the East Asian Crisis. *World Development*, 29(6), pp.1057–1069.

Pollin, R. (2007). Microcredit: False Hopes and Real Possibilities. Foreign Policy Focus, 2.

Porteous, D. (2006). Competition and Microcredit Interest Rates. Focus Note 33. Washington D.C.: CGAP.

Rhyne, E., & Christen, R. (1999). Microfinance Enters the Marketplace. USAID.

Roberts, P.W. (2013). The Profit Orientation of Microfinance Institutions and Effective Interest Rates. *World Development*, 41, pp.120–131.

Roodman, D. & Qureshi, U. (2006). Microfinance as Business. Center for Global Development Working Paper 101. Washington, D.C.: Center for Global Development.

Roodman, D. (2012). *Due Diligence: An Impertinent Inquiry into Microfinance*. Washington, D.C.: Center for Global Development.

Rosenberg, R. (2007). CGAP Reflections on the Compartamos Initial Public Offering: A Case Study on Microfinance Interest Rates and Profits. CGAP Focus Note 42. Washington D.C.: CGAP.

Rosenberg, R., Gonzalez, A. & Narain, S. (2009). The New Moneylenders: Are the Poor Being Exploited by High Microcredit Interest Rates? Occasional Paper 15. Washington D.C.: CGAP.

Rosenberg, R. et al. (2013). Microcredit Interest Rates and Their Determinants 2004 – 2011. Access to Finance FORUM 7. Washington D.C.: CGAP.

Schreiner, M. (2002). Aspects of Outreach: A Framework for Discussion of the Social Benefits of Microfinance. *Journal of International Development*, 14(5), pp.591–603.

Stephens, B. & Tazi, H. (2006). Performance and Transparency: A Survey of Microfinance in South Asia. *MicroBanking Bulletin*, April, pp.22–34.

Stock, J. H., & Watson, M. W. (2008). Heteroskedasticity-robust Standard Errors for Fixed Effects Panel Data Regression. *Econometrica*, 76(1), 155-174.

The SEEP Network (2010). Pocket Guide to the Microfinance Financial Reporting Standards Measuring Financial Performance of Microfinance Institutions. Washington, D.C.: The SEEP Network.

Torres-Reyna, O. (2007). Panel Data Analysis Fixed and Random Effects using Stata (v. 4.2). *Data & Statistical Services, Princeton University*.

Wooldridge, J.M. (2006). *Introductory Econometrics*: *A Modern Approach* 3rd ed., Mason, OH: Thomson Higher Education.

World Bank (2015). Global Financial Development Report 2015-2016: Long Term Finance. Washington, D.C.: World Bank.

Appendix

Table 5: List of Variables

Variable	Description	Source
Institution-specific variables		
Yield	Yield on Gross Loan Portfolio (GLP) (nominal) (%)	MixMarket
Wage	Average Salary / GNI per capita (%)	MixMarket
Persex	Personnel expenses related to operations/GLP	MixMarket
Admex	(Administrative expenses + Depreciation)/GLP	MixMarket
Provex	Provision for Loan Impairment/GLP	MixMarket
Finex	Financial expenses/GLP	MixMarket
Leverage	Debt / Equity Ratio	MixMarket
GLPTA	Gross Loan Portfolio / Total Assets	MixMarket
ROGLP	Return on Gross Loan Portfolio	MixMarket
OSS	Operating Self-Sufficiency (%)	MixMarket
AgeNew	Dummy = 1 if age new	MixMarket
AgeYoung	Dummy = 1 if age young	MixMarket
LogBorr	Number of borrowers (expressed as logarithm)	MixMarket
FemBorr	Number of female borrowers / number of active borrowers	MixMarket
BorrLoanOff	Borrowers / Loan Officers	MixMarket
BorrStaff	Borrowers / Total Staff	MixMarket
LoanBalBorr	Average Loan Balance per Borrower	MixMarket
LogLoansOut	Number of Loans Outstanding (expressed as logarithm)	MixMarket
Staff	Total number of staff members	MixMarket
LoansStaff	Loans per Staff Member	MixMarket
Exogenous variables		
LogGNIpc	Gross National Income per capita, Atlas method (current USD, expressed as logarithm)	World Bank
GNIpcGr	Growth rate of GNI per capita (annual %)	World Bank
Infl	Inflation, consumer prices (annual %)	World Bank
LogPop	Population size of country (expressed as logarithm)	World Bank
PopDens	Population density (people per sq. km of land area)	World Bank
Comp	Competition: Number of active microfinance borrowers / adult population	MixMarket, Author's calculations
DomCr	Domestic credit to private sector (% of GDP)	World Bank

Table 6: Descriptive Statistics for Portfolio Yield Regressions

Variables	Obs	Mean	Std. Dev.	Min	Max
Yield	9,320	0.347	1.035	0.0507	97.84
Wage	8,196	5.214	40.95	0	3,308
Persex	9,056	0.171	2.028	0	191.5
Admex	9,320	0.133	0.852	-0.0658	78.70
Provex	9,320	0.0331	0.690	-2.507	63.27
Finex	9,320	0.0751	0.243	-0.633	19.44
Leverage	9,293	4.612	43.51	-2,478	1,345
GLPTA	9,320	0.764	0.231	0.00420	9.834
ROGLP	9,320	-0.00681	0.554	-45.67	6.029
OSS	9,315	1.171	0.617	-1.276	36.63
AgeNew	9,133	0.106	0.308	0	1
AgeYoung	9,133	0.190	0.392	0	1
LogBorr	8,857	4.012	0.854	0.301	6.829
FemBorr	7,734	0.648	0.264	0	1.256
BorrLoanOff	8,341	322.9	856.3	1	67,418
BorrStaff	8,730	132.6	152.4	0	7,578
LoanBalBorr	8,835	0.782	4.243	0.000800	280.6
LogGNIpc	9,253	3.328	0.423	2.204	4.239
GNIpcGr	9,272	444.5	238.0	1	833
Infl	9,272	473.1	260.8	1	916
LogPop	9,272	7.529	0.747	5.017	9.135
PopDens	9,272	153.1	203.2	1.626	1,222
Comp	9,207	0.0506	0.0558	0	0.239
DomCr	9,272	459.4	234.6	1	925
Number of MFIs	2,039	-	-	-	-

Table 7: Descriptive Statistics for Personnel Expenses Regression

Variable	Obs	Mean	Std. Dev.	Min	Max
Persex	9,056	0.171	2.028	0	191.5
Wage	8,196	5.214	40.95	0	3,308
AgeNew	9,133	0.106	0.308	0	1
AgeYoung	9,133	0.190	0.392	0	1
LoanLoss	8,895	0.0174	0.323	-11.80	25.71
LogLoansOut	8,694	9.298	1.964	1.099	17.69
FemBorr	7,734	0.648	0.264	0	1.256
LoanBalBorr	8,840	2,222	30,789	1	2.534e+06
BorrStaff	8,730	132.6	152.4	0	7,578
Staff	8,900	447.2	1,573	0	34,841
LoansStaff	8,592	829.4	45,173	0	3.007e+06
LogGNIpc	9,253	3.328	0.423	2.204	4.239
GNIpcGr	9,272	444.5	238.0	1	833
LogPop	9,272	7.529	0.747	5.017	9.135
PopDens	9,272	153.1	203.2	1.626	1,222
Infl	9,272	473.1	260.8	1	916
Comp	9,207	0.0506	0.0558	0	0.239
DomCr	9,272	459.4	234.6	1	925
Number of MFIs	2,039	-	-	-	-

Table 8: Hausman Test (with time dummies)

	Coefficients (b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
Wage	.0248364	.023881	.0009554	.0000611
Leverage	-.0002353	-.0003419	.0001066	.0001483
GLPTA	-.0124527	-.092116	.0796633	.027418
ROGLP	.0698183	.0715221	-.0017039	.0065637
OSS	.0135641	.0134364	.0001277	.0088117
AgeNew	-.0042081	.0986228	-.102831	.0429156
AgeYoung	.0458399	.0572534	-.0114135	.0264946
LogBorr	-.2508295	-.0219325	-.228897	.0444208
FemBorr	-.0896807	.1149213	-.204602	.0832273
BorrLoanOff	-1.07e-06	-3.43e-06	2.37e-06	3.68e-06
BorrStaff	-.0000793	-.0002442	.0001649	.000103
LoanOffStaff	.0399291	.0931163	-.0531872	.0528377
LoanBalBorr	-.2969111	-.087236	-.2096751	.0107964
LogGNIpc	-.0514124	.1457393	-.1971516	.1763674
GNIpcGr	7.28e-06	-.000043	.0000502	.0000272
Infl	-.0000118	.0000148	-.0000266	.00002
LogPop	.5452321	.0264464	.5187857	.8423877
PopDens	.0004635	-.000045	.0005085	.0010927
Comp	.3396705	.0391258	.3005448	.4382815
DomCr	.000065	-.0001301	.000195	.0000492
2006bn.Year	.0093996	-.0127598	.0221594	.0150137
2007.Year	.0225386	-.0305348	.0530734	.0259673
2008.Year	.0496323	.0081048	.0415274	.0380964
2009.Year	.044555	-.0298603	.0744154	.0460851
2010.Year	.0642718	.0027549	.061517	.0519276
2011.Year	.059778	-.0193775	.0791555	.0593858
2012.Year	.059668	-.0064086	.0660766	.0689026
2013.Year	.0048293	-.0680575	.0728868	.0759121
2014.Year	.1067907	.0317584	.0750323	.081995

```
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(23) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                           =      408.92
                 Prob>chi2 =      0.0000
```

Table 9: Hausman Test (without time dummies)

	Coefficients (b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
Wage	.0248405	.0238858	.0009547	.000061
Leverage	-.000242	-.0003471	.0001051	.0001483
GLPTA	-.0121536	-.0903137	.0781601	.0273802
ROGLP	.0689439	.0712159	-.0022721	.0065357
OSS	.0137084	.0138164	-.000108	.0087995
AgeNew	-.0073699	.0989798	-.1063497	.0426801
AgeYoung	.0413283	.0573015	-.0159731	.0262067
LogBorr	-.2465661	-.0221931	-.2243731	.0439877
FemBorr	-.0945052	.1151008	-.209606	.0827151
BorrLoanOff	-7.57e-07	-2.72e-06	1.96e-06	3.67e-06
BorrStaff	-.000091	-.0002452	.0001542	.0001027
LoanOffStaff	.0287594	.0886313	-.0598719	.052345
LoanBalBorr	-.2968466	-.0871434	-.2097032	.0107855
LogGNIpc	.0393912	.1449189	-.1055277	.1221387
GNIpcGr	-2.69e-06	-.0000372	.0000345	.0000234
Infl	-9.43e-06	.0000182	-.0000277	.0000188
LogPop	.8205963	.0254978	.7950985	.7255541
PopDens	.0005801	-.0000439	.000624	.0010774
Comp	.411777	.028664	.383113	.4246523
DomCr	.0000622	-.0001305	.0001926	.000047

```
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(14) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                           =      401.81
                Prob>chi2 =       0.0000
```

Table 10: Wald Test Time Dummy Variables

```
 ( 1)  2006.Year = 0
 ( 2)  2007.Year = 0
 ( 3)  2008.Year = 0
 ( 4)  2009.Year = 0
 ( 5)  2010.Year = 0
 ( 6)  2011.Year = 0
 ( 7)  2012.Year = 0
 ( 8)  2013.Year = 0
 ( 9)  2014.Year = 0

       F(  9,  1833) =    15.73
            Prob > F =    0.0000
```

Table 11: Correlation Matrix

	Yield	Wage	Leverage	GLPTA	ROGLP	OSS	AgeNew
Yield	1.0000						
Wage	0.8805*	1.0000					
Leverage	-0.0056	0.0040	1.0000				
GLPTA	-0.0213	-0.0155	0.0144	1.0000			
ROGLP	0.1144*	0.0975*	0.0045	0.1122*	1.0000		
OSS	-0.0024	-0.0143	-0.0103	0.0980*	0.1726*	1.0000	
AgeNew	0.0227	0.0001	0.0148	-0.0351*	-0.0559*	-0.0265	1.0000
AgeYoung	0.0176	-0.0033	-0.0100	-0.0013	-0.0075	-0.0028	-0.1664*
LogBorr	-0.0141	-0.0010	0.0019	0.0996*	0.0656*	-0.0201	-0.1869*
FemBorr	0.0242	-0.0172	0.0103	0.0663*	-0.0003	-0.0495*	0.0122
BorrLoanOff	-0.0132	-0.0024	-0.0003	0.0136	0.0133	0.0075	-0.0239
BorrStaff	-0.0182	-0.0046	0.0076	0.0970*	0.0293*	0.0375*	-0.0147
LoanBalBorr	-0.0134	0.0498*	0.0018	-0.0224	0.0065	0.0359*	0.0578*
LogGNIpc	0.0312*	-0.0369*	-0.0124	0.1488*	0.0291*	0.0508*	-0.0768*
GNIpcGr	-0.0178	-0.0131	0.0259	0.1173*	0.0314*	0.0528*	0.0205
Infl	-0.0047	-0.0141	0.0183	0.0314*	0.0156	-0.0212	-0.0041
LogPop	0.0051	-0.0298*	0.0357*	0.0703*	-0.0036	-0.0074	0.0586*
PopDens	-0.0339*	-0.0239	0.0243	0.0748*	0.0084	-0.0094	-0.0213
Comp	-0.0155	-0.0037	0.0019	0.1106*	0.0390*	0.0297*	-0.1448*
DomCr	-0.0248	-0.0107	0.0032	0.1424*	0.0084	0.0135	-0.0698*

	AgeYoung	LogBorr	FemBorr	BorrLo~f	BorrSt~f	LoanBa~r	LogGNIpc
AgeYoung	1.0000						
LogBorr	-0.1059*	1.0000					
FemBorr	0.0266	0.2985*	1.0000				
BorrLoanOff	-0.0276	0.1172*	0.0498*	1.0000			
BorrStaff	-0.0108	0.3141*	0.2573*	0.2950*	1.0000		
LoanBalBorr	0.0105	-0.1005*	-0.2560*	-0.0256	-0.0711*	1.0000	
LogGNIpc	-0.0407*	-0.1690*	-0.1606*	-0.0174	-0.0865*	-0.0364*	1.0000
GNIpcGr	-0.0037	0.0787*	0.1570*	0.0165	0.0809*	0.0261	0.0060
Infl	0.0092	0.0431*	0.1369*	0.0054	0.0322*	-0.0076	-0.0603*
LogPop	0.0525*	0.2363*	0.3931*	0.0654*	0.2176*	-0.0421*	-0.0320*
PopDens	-0.0444*	0.3154*	0.3618*	0.0360*	0.1504*	-0.0438*	-0.2844*
Comp	-0.1451*	0.2906*	0.0385*	0.0313*	-0.0232	-0.0195	0.0793*
DomCr	-0.0501*	0.1143*	0.1422*	0.0291*	0.0939*	-0.0359*	0.1723*

	GNIpcGr	Infl	LogPop	PopDens	Comp	DomCr
GNIpcGr	1.0000					
Infl	0.1069*	1.0000				
LogPop	0.3380*	0.1471*	1.0000			
PopDens	0.2387*	0.1584*	0.4170*	1.0000		
Comp	0.0974*	-0.0189	-0.1716*	0.2198*	1.0000	
DomCr	0.0640*	0.0962*	0.0946*	0.1786*	0.0835*	1.0000

Note: * p<0.01

Table 12: Portfolio Yield on Average Salaries (full table)

VARIABLES	(1) Baseline	(2) MFI-specific	(3) Exogenous	(4) All
Wage	0.0243***	0.0248***	0.0243***	0.0248***
	(0.00598)	(0.00506)	(0.00598)	(0.00505)
ROGLP		0.0690		0.0695
		(0.0683)		(0.0686)
Leverage		-0.000237**		-0.000239**
		(0.000109)		(0.000111)
GLPTA		-0.0125		-0.0122
		(0.0199)		(0.0208)
OSS		0.0136		0.0137
		(0.0121)		(0.0121)
AgeNew		-0.00286		-0.00444
		(0.0357)		(0.0343)
AgeYoung		0.0467		0.0456
		(0.0413)		(0.0399)
LogBorr		-0.236		-0.249
		(0.176)		(0.189)
FemBorr		-0.0839		-0.0881
		(0.119)		(0.119)
BorrLoanOff		-1.61e-06		-1.76e-06
		(1.24e-06)		(1.44e-06)
BorrStaff		-8.29e-05		-7.28e-05
		(5.22e-05)		(5.43e-05)
LoanBalBorr		-0.294		-0.297
		(0.224)		(0.228)
LogGNIpc			0.0974	-0.0513
			(0.0698)	(0.182)
GNIpcGr			-1.51e-05*	7.29e-06
			(8.50e-06)	(2.38e-05)
Infl			-4.48e-06	-1.21e-05
			(6.76e-06)	(1.49e-05)
LogPop			0.730***	0.516
			(0.244)	(0.481)
PopDens			0.000157	0.000469
			(0.000233)	(0.000607)
Comp			-0.305***	0.345
			(0.117)	(0.620)
DomCr			-5.61e-07	6.50e-05
			(1.88e-05)	(6.25e-05)
Year controls	Yes	Yes	Yes	Yes
Constant	0.225***	1.355	-5.561***	-2.402
	(0.0358)	(0.867)	(1.909)	(4.153)
Observations	8,196	6,837	8,107	6,763
R-squared	0.822	0.846	0.822	0.846
Number of ID	1,876	1,648	1,863	1,636

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Average Salaries as Determinant of Personnel Expenses

To test the assumed relationship between average salaries and personnel expenses the model is constructed. The baseline model is extended in additional regressions with loan-specific, MFI-specific and exogenous control variables. Additional controls are introduced to further analyze personnel expenses: the number of loans outstanding expressed as logarithm (LogLoanOut), the total number of staff member (Staff) and the loans per staff member (LoansStaff).

This leads to the (simplified) equation:

$$6)\ Persex_{\mathrm{it}} = \beta_0 + \beta_1 Wage_{\mathrm{it}} + \beta_2(Loan - specific_{\mathrm{it}}) + \beta_3(MFI - specific_{\mathrm{it}}) + \beta_4(Exogenous_{\mathrm{it}}) + Year_{\mathrm{t}} + a_{\mathrm{i}} + u_{\mathrm{it}}$$

where $Persex_{\mathrm{it}}$ represents the dependent variable personnel expenses for MFI i in time period t. $\beta_1 Wage_{\mathrm{it}}$ is the main term of interest with average salaries as independent variable and β_1 the coefficient of interest. Several loan-specific and MFI-specific controls, which could influence personnel expenses, are included. The same exogenous controls, time dummies and error terms as in equation (1) and (2).

The results of the regression of personnel expenses on average salaries are presented in table 13. In the baseline regression, average salaries show a highly statistically significant positive relationship with personnel expenses. The coefficient, introduced as β_1 in section 3.4, shows that with an increase of average salaries over GNI p.c. (both in USD) by one unit, personnel expenses (expressed as a ratio to GLP) increase by 0.0478 units. Since the average salaries vary so much between MFIs (a mean of 5.2 with standard deviation of 41.0, as outlined in the descriptive statistics table 6 in the appendix), this can transfer to large differences in the personnel expense ratio. The baseline includes 8,196 observations from 1,846 MFIs and the R^2 shows that the model accounts for 82.7% of variation in the dependent variable.

In regression (2), loan-specific controls are added to the baseline to see whether different characteristics of loans will change the variable of interest. The coefficient for average salaries increases slightly to 0.0504, whereas the included controls are all not statistically significant. In (3), some of the already from the previous model familiar MFI-specific controls, which are assumed to have a relation to personnel expenses, are appended. The coefficient for average salaries increases again slightly to 0.0527 with number of loans, the average loan size, borrowers to staff, total number of staff and loans per staff member as the statistically significant control variables. The coefficients of the time dummies are now all statistical significant and positive. With the inclusion of more variables, more of dependent variable variation is explained as R^2 rises to 92.6%. The addition of the familiar exogenous control variables (with competition being the only statistically significant exogenous variable) in (4) and (5) leaves the previous regression results unchanged.

Table 13: Personnel Expenses on Wages

VARIABLES	(1) Baseline	(2) Loan-specific	(3) MFI-specific	(4) Exogenous	(5) All
Wage	0.0478***	0.0504***	0.0527***	0.0478***	0.0527***
	(0.0117)	(0.00809)	(0.00469)	(0.0117)	(0.00465)
AgeNew			-0.00814		-0.0237
			(0.0456)		(0.0462)
AgeYoung			0.0127		0.0154
			(0.0286)		(0.0295)
LoanLoss			-0.225		-0.222
			(0.243)		(0.241)
LogLoansOut		-0.0933*	-0.190***		-0.208***
		(0.0527)	(0.0655)		(0.0725)
FemBorr		-0.406	-0.366*		-0.350*
		(0.320)	(0.200)		(0.197)
LoanBalBorr		-0.000205	-0.000443**		-0.000447**
		(0.000170)	(0.000190)		(0.000191)
BorrStaff			-0.000254**		-0.000218**
			(0.000127)		(0.000111)
Staff			4.89e-05**		4.39e-05**
			(2.33e-05)		(2.03e-05)
LoansStaff		3.05e-07*	6.58e-07***		7.20e-07***
		(1.83e-07)	(2.29e-07)		(2.55e-07)
LogGNIpc				0.0235	0.179
				(0.0352)	(0.122)
GNIpcGr				-1.63e-05	5.42e-05
				(1.42e-05)	(4.15e-05)
LogPop				-0.00910	0.0220
				(0.0257)	(0.0487)
PopDens				-0.000377*	-0.000966
				(0.000228)	(0.00106)
Infl				-1.76e-06	-4.13e-06
				(7.12e-06)	(3.86e-05)
Comp				-0.263*	2.246**
				(0.155)	(1.105)
DomCr				2.27e-05	4.59e-05
				(2.66e-05)	(5.05e-05)
Year controls	Yes	Yes	Yes	Yes	Yes
Constant	-0.0903	1.190	2.230***	-0.0350	1.682**
	(0.0677)	(0.770)	(0.829)	(0.193)	(0.682)
Observations	8,196	7,042	6,829	8,107	6,750
R-squared	0.827	0.872	0.925	0.827	0.926
Number of ID	1,846	1,702	1,619	1,834	1,607

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1