



Network for Studies on Pensions, Aging and Retirement

**Netspar** THESES

*Rients Jan Galema*

**Microfinance as a Socially Responsible  
Investment**

PhD Thesis 2011-019

# Microfinance as a Socially Responsible Investment

Rients Jan Galema

Publisher: University of Groningen, Groningen, The Netherlands

Printed by: Ipskamp Drukkers  
P.O. Box 333  
7500 AH Enschede  
The Netherlands

ISBN: 978-90-367-5026-4 / 978-90-367-5027-1

© 2011 Rients J. Galema

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system of any nature, or transmitted in any form or by any means, electronic, mechanical, now known or hereafter invented, including photocopying or recording, without prior written permission of the publisher.



rijksuniversiteit  
groningen

# Microfinance as a Socially Responsible Investment

**Proefschrift**

ter verkrijging van het doctoraat in de  
Economie en Bedrijfskunde  
aan de Rijksuniversiteit Groningen  
op gezag van de  
Rector Magnificus, dr. E. Sterken,  
in het openbaar te verdedigen op  
donderdag 15 september 2011  
om 16.15 uur

door

Rients Jan Galema

geboren op 23 mei 1984  
te Nijefurd

Promotores: Prof. dr. B.W. Lensink  
Prof. dr. L. Spierdijk

Beoordelingscommissie: Prof. dr. T. Beck  
Prof. dr. C.L.M. Hermes  
Prof. dr. J.J. Morduch

# Acknowledgements

Probably the most read part of a PhD thesis is the Acknowledgements section. For most PhDs it serves a dual purpose: to acknowledge those who were important in writing the thesis and to thank all other people that were important while writing the thesis (as they are also in the audience on the day of the defence). I'll do something similar and tell you about the experiences I had during my PhD time.

Once I was at a conference talking to a Belgian colleague who had finished his thesis a couple of years ago. He told me that writing his PhD thesis had been quite a struggle. I decided to tease him a little bit and told him I thought that writing a PhD thesis was like a four-year paid holiday in which you can exercise your hobby and have all the freedom to do the research you like. Fortunately, he laughed about the tease, and although I exaggerated, I have been very fortunate that I did not have to deal with any major setbacks during my PhD period.

Actually, I had most difficulties in writing chapter 2 of this thesis. This was the first research I did as part of my research master and at that time I was really struggling to combine everything I had learned about doing research in an actual article. At times I even doubted whether I would be able to write a whole PhD thesis. Fortunately, Auke Plantinga en Bert Scholtens really supported my first steps into research, for which I am very grateful.

Next, I started doing research with my promotors Robert Lensink and Laura Spierdijk. Already at the start, we enjoyed homemade dinners together. I have very fond memories of these dinners, as they immediately made me feel welcome to my new working environment. In addition, they make a very good team of supervisors, because their skills are complementary. Without Robert's knowledge of microfinance and overview of the research's big picture and Laura's knowledge of econometrics and her keen eye for details this thesis would not have existed. I am very grateful for their help and support.

Many other people were important in writing this thesis. Roy Mersland was

involved in writing chapter 5. I thank him for providing data and valuable insights into microfinance practice. In addition, I am very thankful to Lammertjan Dam for providing the ideas that lead to chapter 4, Rob Alessie for his suggestion to use quantile regression in chapter 5 and Aljar Meesters for downloading the MixMarket dataset I used in several chapters. Tomek was a very effective sounding board for my ideas as well as a very pleasant roommate. I benefited a lot from his knowledge of econometrics and we shared many laughs.

A special thanks goes to the secretaries of the Finance group, Grietje and Ellie, and the PhD coordinators, Martin Land and Linda Toolsema, for providing information and assistance in arranging many things in the years I was a PhD candidate. In general, my colleagues provided a very pleasant atmosphere. I enjoyed the many times I had lunch with my colleagues from the 8th floor and I especially have fond memories of the coffee breaks I shared with Aljar Meesters, Allard van der Made, Bastiaan Overvest, Eelco Zandberg, Lammertjan Dam, Peter Dijkstra, Pim Heijnen, Remco van Eijkel and Tomek Katzur. Finally, I would like to thank Thorsten Beck, Niels Hermes and Jonathan Morduch for reading the manuscript.

Outside academia I have been active in Sailing Association Aeolus, Fanfare Orchestra CWO, Bigband Stageband and several other ad hoc music projects. Sailing and music offered plenty distraction for me to stay a motivated writer and I have fond memories of all the people I sailed and played music with. A special thanks goes to Wytze van der Zweep. He and I go back a long time and he introduced me to Aeolus, where I have found many good friends. Another special thanks goes to the members of the board of Fanfare Orchestra CWO: Anneke Adema, Eduard Witteveen, Klaas Kuperus, Jelmer Lok and Johanna bij de Leij. I was very fortunate to be chairman of a board composed of such motivated people. In chapter 5 I argue that diversity of opinions leads to more balanced decisions. In practice I found that taking into account your diverse opinions not only made decisions more balanced, but also improved them. Especially when we experienced some setbacks, we were able to keep going as a group. This meant a lot to me.

Because I like to be involved in lots of activities, I did not always free up a lot of time for my family. Nonetheless, my family has always been around and willing to help me. As academics are not always the most practical people, I was especially happy that I could always count on them. Thank you Folkert and Willy, Tineke and Gerben-Jan and Gerbrich for your continuing support.

# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	Aim . . . . .	4
1.2	Socially responsible investment . . . . .	6
1.3	Microfinance investment . . . . .	8
1.4	Is microfinance good for the poor? . . . . .	9
1.5	Why invest in microfinance? . . . . .	11
1.6	Trade-off between financial and social objectives . . . . .	12
1.7	Microfinance risks . . . . .	13
1.8	Summary . . . . .	16
<b>2</b>	<b>The stocks at stake: return and risk in socially responsible investment</b>	<b>19</b>
2.1	Introduction . . . . .	19
2.2	Background . . . . .	21
2.3	Data & Method . . . . .	22
2.3.1	Data . . . . .	22
2.3.2	SRI Portfolios . . . . .	24
2.3.3	Fama-MacBeth regressions . . . . .	27
2.3.4	Book-to-market regressions . . . . .	29
2.4	Results . . . . .	30
2.4.1	SRI portfolios . . . . .	30
2.4.2	Fama-MacBeth regressions . . . . .	31
2.4.3	Book-to-market regressions . . . . .	39
2.4.4	Robustness . . . . .	41
2.5	Conclusions . . . . .	41
<b>3</b>	<b>International diversification and microfinance</b>	<b>43</b>
3.1	Introduction . . . . .	43

3.2	Literature survey . . . . .	46
3.3	Methodology . . . . .	47
3.4	Data . . . . .	49
3.5	Results . . . . .	53
3.6	Conclusions . . . . .	58
<b>4</b>	<b>Social investment in microfinance</b>	<b>61</b>
4.1	Introduction . . . . .	61
4.2	Data . . . . .	63
4.3	The risk-return-outreach trade-off . . . . .	64
4.4	Quantifying the risk-return-outreach trade-off . . . . .	66
4.5	Conclusion . . . . .	73
4.A	Methodology appendix . . . . .	75
<b>5</b>	<b>Do powerful CEOs determine microfinance performance?</b>	<b>77</b>
5.1	Introduction . . . . .	77
5.2	Theoretical background . . . . .	79
5.2.1	Diversification of opinions . . . . .	79
5.2.2	Managerial discretion . . . . .	80
5.2.3	Measures of CEO power . . . . .	82
5.2.4	Agency and organization theory's effect on performance . . . . .	83
5.3	Hypotheses development . . . . .	84
5.3.1	Microfinance context . . . . .	84
5.3.2	Moderating effect of organization type on CEO power . . . . .	88
5.4	Methodology . . . . .	91
5.4.1	Sample . . . . .	91
5.4.2	Methods . . . . .	93
5.4.3	Dependent variable . . . . .	95
5.4.4	Independent variables . . . . .	95
5.4.5	Control variables . . . . .	96
5.5	Analyses and results . . . . .	104
5.6	Discussion . . . . .	107
5.7	Conclusion . . . . .	109
<b>6</b>	<b>Debt enforcement and microfinance risk</b>	<b>111</b>
6.1	Introduction . . . . .	111
6.2	Theoretical background . . . . .	115

6.2.1	Bank risk: the effect of debt enforcement, creditor rights and information sharing . . . . .	115
6.2.2	MFIs: the effect of debt enforcement, creditor rights and information sharing . . . . .	117
6.2.3	The moderating effect of creditor rights and legal origin . . . . .	119
6.2.4	The moderating effect of MFI type . . . . .	119
6.2.5	Portfolio growth . . . . .	120
6.3	Data and summary statistics . . . . .	121
6.3.1	The sample . . . . .	121
6.3.2	Debt enforcement inefficiency, creditor rights and information sharing measures . . . . .	122
6.3.3	Z-score: measuring MFI risk . . . . .	129
6.3.4	Bank regulation controls, bank controls and macro controls . . . . .	130
6.4	Results . . . . .	131
6.4.1	Hypothesis 1: the effect of credit institutions on MFI risk . . . . .	131
6.4.2	Hypothesis 2: the moderating effect of creditor rights and legal origin . . . . .	133
6.4.3	Hypothesis 3: the moderating effect of MFI type . . . . .	137
6.4.4	Hypothesis 4: the effect of credit institutions on portfolio growth	141
6.5	Robustness checks . . . . .	142
6.5.1	Z-score disaggregation and alternative MFI risk measures . . . . .	142
6.5.2	Robustness checks: weighted regressions and country level regressions . . . . .	146
6.6	Conclusion . . . . .	147
6.A	Appendix . . . . .	149
6.A.1	Appendix A.1 . . . . .	149
6.A.2	Appendix A.2 . . . . .	149
<b>7</b>	<b>Conclusion</b> . . . . .	<b>161</b>
7.1	Summary . . . . .	161
7.2	Implications and limitations . . . . .	163
	<b>References</b> . . . . .	<b>167</b>
	<b>Samenvatting (Summary in Dutch)</b> . . . . .	<b>179</b>



## *Chapter 1*

# Introduction

In 1967, as the Vietnam War is raging, a US reverend named Luther E. Tyson receives a letter from a woman in Ohio asking whether he knows of any mutual fund that does not invest in war-related industries. He realizes that no such mutual fund exists, so he decides to create one. In 1971, starting with \$101,000, he and three cofounders develop one of the world's first mutual funds dedicated to both the social and financial well-being of its investors: the Pax World Fund. Little could Tyson have known that the Pax World Fund would help give birth to the socially responsible investment (SRI) movement. Since 1971, interest in the SRI industry has expanded exponentially, such that today 11% of the \$25.1 trillion in total assets under professional management in the US is involved in socially responsible investing (SIF, 2007).

Around the time the Pax fund is created in the US, a fierce war results in the independence of Bangladesh from Pakistan in December 1971. After the war, US trained economist Muhammad Yunus returns to his home country to teach at Chittagong University in southeast Bangladesh. After the famine of 1974, he becomes disillusioned with his career as an economics professor and decides to start experimenting with lending to poor households. Although his personal means are limited, he finds that even small loans are sufficient for villagers to run small profitable businesses. Surprisingly, borrowers are not only profiting from his lendings, but are also able to repay him reliably, even though they have no collateral. In subsequent years Yunus expands his experiment of lending to the poor, which results in the creation of one of the first microfinance institutions (MFIs), the Grameen bank, in 1983. The success of the Grameen bank soon creates follow-ups in other countries such that today MFIs are helping millions of poor all over the world.

Both Luther E. Tyson and Muhammad Yunus were the first in supplying a financial service for which there appeared to be a huge demand and both were socially, instead of financially, motivated to do so. Yet, it is not until the beginning of the 1990s that these stories become connected, but first we go a bit further back in time. In the 1970s, before Muhammad Yunus started the microfinance experiment, state-run banks served the poor, usually with a focus on farmers. These state-run banks were not very efficient in reaching the poor. They required large subsidies and were not cost-effective: to obtain political goodwill they charged too low interest rates and collected loan repayments only half-heartedly. Moreover, due to fluctuating weather conditions and crop prices their success was impaired by the inherent risk of agricultural lending.<sup>1</sup>

As microfinance pioneers start lending to the poor at the beginning of the 1980s, they shift the focus from agricultural lending towards non-farm lending. Non-farm lending is less risky, because handicraft producers and small storeowners receive a fairly steady stream of income. In addition, microfinance pioneers develop new lending practices to alleviate the problem that the poor lack collateral. The most famous of these lending practices is group lending in which group lenders are required to guarantee each other's loan repayments. Other lending practices include awarding incrementally larger loans upon each successful repayment and denying defaulters access to future loans. These lending practices have helped MFIs achieve repayment rates of sometimes more than 95%.

These high repayment rates made policy makers realize that MFIs could be profitable—or as they phrased it: 'MFIs could be financially sustainable.' Due to the limited availability of subsidies, donors encouraged MFIs to use subsidies only in the start-up phase after which sufficiently high interest rates should make MFIs independent of subsidies. Instead of running on subsidies, the ultimate goal of MFIs should be to become for-profit institutions that rely on private investors to supply funding. By the early 1990s, the thrust towards financial sustainability resulted in MFIs like Bancosol in Bolivia to reach sufficient scale to transform into for-profit institutions (Rhyne, 2009). In 2007, Banco Compartamos of Mexico held an initial public offering in which insiders sold 30 percent of their stocks. The sale was very successful and Compartamos was soon worth \$1.6 billion.

This is where the stories of Luther E. Tyson and Muhammad Yunus come together. Whereas microfinance used to be the terrain of donor agencies and phil-

---

<sup>1</sup> Note that even though state-run banks were not very efficient, recent evidence by Burgess and Pande (2005) suggests that opening branches in rural unbanked locations in India was associated with a reduction in rural poverty

anthropists, the commercialization of microfinance made it possible for socially responsible investors to invest in microfinance. About 40 to 80 percent of the developing world population is still unbanked (World Bank, 2007), so the capital supplied by socially responsible investors could allow the provision of loans to millions of poor currently without access to banks or exploited by loan sharks. Nonetheless, Muhammad Yunus (2007, p.1) did not celebrate the marriage of socially responsible investment and microfinance. In response to the initial public offering (IPO) of Banco Compartamos of Mexico he replied: "I am shocked by the news about the Compartamos IPO. Microcredit should be about helping the poor to get out of poverty by protecting them from the moneylenders, not creating new ones." Yunus compares Compartamos to traditional moneylenders, because Compartamos's customers were paying interest rates of 86 percent per year on loans (Rosenberg, 2007). These high interest rates have boosted Compartamos' profits: in 2005, 24% of Compartamos interest revenue was pure profit. Although these high profits allowed Compartamos to go public and obtain funding to help thousands of extra borrowers, instead it could also have chosen to refrain from going public and charge lower interest rates.

Ultimately it boils down to a trade-off: should MFIs commercialize to become for-profits that serve more borrowers, or should they expand at a slower pace as not-for-profits? Essentially, this is as much a general question as it is a question that each MFI has to answer for itself, because Cull et al. (2009) show there is room for both commercial and not-for-profit microfinance. For-profits serve the largest total amount of loans, although without subsidy they are less well equipped to serve the poorest of the poor. By contrast, not-for-profits currently still serve most of the world's poor with the smallest average loan sizes. As they are subsidized, they remain best suited to serve the poorest of the poor. Still, despite not-for-profits' continued importance, the huge gaps in access to finance allow ample opportunities for commercial MFIs to further expand and serve the somewhat less poor.

Implicitly, the discussion assumes that increasing the supply of finance to fill the huge gaps, will necessarily lead to more economic development of the poor. Yet, impact studies (e.g. Banerjee et al., 2010; Karlan and Zinman, 2010a and 2010b) do not show that there is an unequivocally positive effect of microfinance on poverty reduction. Instead, the poverty reducing effect of microfinance is heterogenous: it does not always have a positive effect and is not necessarily most beneficial to female borrowers. There are even authors, most notably Bateman (2010), that suggest that microfinance works against economic development. Although much of

his reasoning is based on anecdotal evidence, in a nutshell he argues that microfinance finances informal economic activity without growth potential, which goes at the expense of the development of sectors that do have growth potential (e.g. small and medium sized firm finance). Commercialization exacerbates the negative effects of microfinance, because it leads to an oversupply of credit to poor clients working in the same type of businesses like petty trade and subsistence farming. The resulting increase of competition further depresses the growth potential of the poor's enterprises.

So both commercialization of microfinance and the role of microfinance in economic development are not undisputed. Still, we learn more and more about how financial markets work in developing countries. Increasingly, financial initiatives are being put to the test through randomized control experiments and are adapted when they do not work. These experiments could shift the focus of non-profit microfinance towards other financial services. At the same time, it is hard to imagine that profitable for-profit microfinance would cease to exist. To the extent that microfinance institutions cannot fully finance themselves by offering savings, there will always be a need for socially responsible investment in microfinance. This thesis contributes to understanding microfinance as a socially responsible investment.

## 1.1 Aim

The main aim of this thesis is to contribute to the discussion on the advantages and disadvantages of microfinance commercialization from an investor's perspective. Whereas most research has focused on whether microfinance helps to get people out of poverty, the lack of studies on microfinance investment motivates us to investigate microfinance from an investor perspective, using tools and techniques from mainstream finance research.

The main question is: What motivates investors to invest in microfinance? One motivation can be purely financial. Therefore, we investigate whether microfinance offers diversification advantages and what determines the risk of a microfinance investment. Investors can also be socially motivated to invest in microfinance. Yet, to the extent that they face a trade-off between outreach to the poor and financial returns, investors have to balance return, risk and outreach. We try to find out to what extent they can optimally balance their portfolio with respect to these three objectives.

The main focus is on microfinance investment, but we also investigate socially responsible investment in the US. To many investors microfinance is a typical socially responsible investment, which is an investment strategy that incorporates social as well as financial considerations in the investment process. The question whether investors should invest in microfinance belongs to the broader question whether investors should invest socially responsible. According to proponents of socially responsible behavior, SRI could prevent future conflicts—legal or otherwise—and thereby reduce risk. According to a famous opponent of social responsibility, Milton Friedman (1970), the only social responsibility of the firm is to maximize profits. To do otherwise implies that the firm is spending profits that belong to the shareholders. In addition, excess demand for socially responsible stocks increases their price and therefore depresses their return. Therefore, a second question is: What is the effect of a socially responsible investment strategy on the financial performance of an investor's portfolio?

If we would observe this effect in an efficient market like the US, it serves as a lower bound to the effect we could observe in the microfinance investment market. The microfinance investment market is not a public market: most MFIs are not listed on a stock exchange and usually do not own publicly tradable debt. Socially motivated excess demand could cause an oversupply of funding, resulting in MFIs overborrowing to their clients. The absence of a public market for microfinance implies that market prices do not provide timely feedback on the adverse consequences of excess demand.

The absence of a public market for microfinance investment creates several complications in researching microfinance investment. First, we cannot use market returns to evaluate a microfinance investment and have to rely on book returns instead. Some of the techniques from finance, like mean-variance spanning and Markowitz' portfolio optimization, are meant to be used for market returns. We use book returns instead, although we realize they are only a proxy for market returns. Second, because MFIs are not listed, investors almost never invest directly in microfinance, but use an investment fund as intermediary. Return data on investment funds is unfortunately not widely available, so we use the MFI's returns instead. Third, many MFIs are still nonprofit institutions. We focus mostly on financial performance and risk measures based on financial performance, whereas social performance is important to nonprofit MFIs as well.

This thesis takes the perspective that MFIs are developing towards becoming commercialized institutions that are attractive for investors, even though not all

MFI's have the desire to commercialize. Our perspective seems to warrant the use of tools from mainstream finance research, despite data limitations that make their application far from perfect. Still, we believe the approach in this thesis is a valuable first step in analyzing microfinance as a socially responsible investment.

The remainder of this introduction proceeds as follows. First, section 1.2 introduces socially responsible investment and its consequences for prices and returns. Second, section 1.3 introduces microfinance investment. Third, we position the microfinance chapters in the microfinance literature, starting with section 1.4, which introduces studies on microfinance and the poor. Fourth, section 1.5 introduces MFI-level studies and introduces microfinance as a diversification opportunity. Fifth, section 1.6 introduces the trade-off between risk, return and outreach. Sixth, section 1.7 considers the risks of microfinance investment in more detail. Finally, section 1.8 provides a short summary of this introduction.

## 1.2 Socially responsible investment

Microfinance investment belongs to the realm of socially responsible investment. Socially responsible investment has experienced a large growth over the past decade. In the US, professionally managed SRI asset portfolios grew with 324% from \$639 billion in 1995 to \$2.71 trillion in 2007. In comparison, the broader universe of assets under professional management increased less than 260 percent from \$7 trillion to \$25.1 trillion over the same period (SIF, 2007). Also the European market for SRI is growing very rapidly with funds under professional management growing from 1.033 trillion in 2005 to 2.665 trillion in 2007 (Eurosif, 2008).

The public increasingly demands firms to take responsibility for the effect of their actions on society. For instance, the introduction of emissions trading demands firms to pay for the detrimental effects of their pollution. Also the current financial crisis illustrates that short term financial interests do not always match society's interests. In many financial institutions corporate governance did not guard against excessive risk taking, so, today, good governance is high on the agenda of governments and investors worldwide. To change company behavior, public and private investors increasingly realize that they can steer companies towards more socially responsible behavior. Private investors invest in socially responsible mutual funds and public investors like the Dutch pension fund ABP have integrated social, environmental and ethical criteria in their investment process.

Socially responsible investors base their investments also on non-financial cri-

teria, because they want their investments to be consistent with their values (Domini, 2001). Whereas ordinary investors want their companies to maximize shareholder value, socially responsible investors want them to maximize the broader concept of stakeholder value. Shareholder and stakeholder values are not always consistent due to the existence of economic externalities. For instance, polluting companies could maximize shareholder value, but not stakeholder value when they do not internalize their pollution costs. To make investments consistent with values, the oldest and most basic SRI strategy is based on negative screening, which is the practice of excluding stocks from the portfolio that are not consistent with the values of the socially responsible investor. A typical screening strategy excludes stocks involved in alcohol, gambling, tobacco and defense industries, or companies with poor performance in labor relations or environmental protection.

A second goal of socially responsible investors is for their investments to create positive social change (Domini, 2001). Companies create positive social change when they, for instance, invest in the communities in which they operate, stimulate cultural diversity in their workforce or use renewable energy in their production process. To stimulate positive social change, socially responsible investors use positive screening, which consists of selecting companies that meet superior social responsibility standards. Often positive screening is combined with a 'best in class' approach in which only socially responsible outperformers from each industry or market sector are selected. Finally, some funds combine positive and negative screening with shareholder activism to try and make companies more socially responsible by using their voting rights at Annual General Meetings.

In addition to positive screening and social shareholder activism, investors can concentrate their investments in those sectors that promote social change. This allows investors to align their investments with their values in an active way, not just through passive screening. For instance, socially responsible investors concerned with the environment could invest in renewable energy sources like wind and solar energy and investors concerned with world poverty could invest in microfinance. Private investors that want to promote social change in specific areas, and institutional investors that want to show their investees concrete examples of socially responsible investment, could prefer this approach

When investors have non-financial motivations to invest in certain financial assets, socially responsible firms obtain too much funding. SRI increases the price and therefore lowers the cost of capital of socially responsible firms. Several examples show that many investors also view investments as consumption goods. Some in-

vestors hold too much of their employer's stock from a sense of loyalty (Cohen, 2009) and home bias motivates investors to hold mainly assets of companies from their own country or region (French and Poterba, 1991). Still, most standard assets pricing models do not incorporate these effects. They assume that investors are only concerned with the payoffs from their portfolio and that financial assets are not also consumption goods.

When assets are viewed as consumption goods, prices of assets that are popular increase compared to those that are less popular. Consequently, the expected returns of popular assets are lower than those of less popular assets. Fama and French (2007) give two conditions under which such a situation can persist even when there are informed investors, who do not base their investment decisions on tastes. First, informed investors should be willing to hold the complement of taste-based investors. Second, taste-based investors should be willing to accept lower returns as the price of their tastes. For instance, some investors like to hold the stocks of strong companies (growth stocks) and dislike holding distressed (value) stocks. Consequently, the expected returns of growth stocks are lower than those of value stocks.

Socially responsible investment decisions are perhaps the most extreme form of investor tastes, because they are—or at least could be—entirely unrelated to risk and return. In chapter 2 we investigate the aggregate market consequences of socially responsible investment strategies. Hong and Kacperczyk (2009) show that socially irresponsible stocks are undervalued such that they demand a positive risk-adjusted return. In chapter 2 we analyze the prices and returns of socially responsible stocks. We expect socially responsible stocks to be overvalued, and therefore that they earn a negative risk-adjusted return.

### 1.3 Microfinance investment

Microfinance as a socially responsible investment class has gained increased attention. Foreign capital investment in microfinance exceeded \$ 10 billion in December 2008 (Reille et al., 2009). One of the most common ways to invest in microfinance is through a microfinance investment vehicle (MIV), which is a private entity that acts as intermediary between investor and MFI. Although there are examples of direct investment in microfinance, most investors prefer MIVs for the benefit of their capacity to conduct due diligence and monitoring and the benefit of diversification across many MFIs, countries and currencies. Currently there are 103 microfinance

investment vehicles (MIVs) that manage about \$6.6 billion (Reille et al., 2009) and offer fixed income, equity or mixed investment options.

Traditionally, MIVs have supplied mostly debt funding, but for investors that seek financial returns it has become increasingly unattractive to invest in microfinance debt. Out of 10,000 MFIs, most commercial funding flows to the 100 top tier MFIs. Currently there is too much debt capital compared to the number of deals available ([www.iamfi.com](http://www.iamfi.com)). Moreover, many eligible MFIs are already highly leveraged or want to decrease leverage to improve solvability in light of the global economic slowdown. Thus, MIVs have recently started to supply more equity funding. The process of commercialization also increases demand for equity funding, as many MFIs become regulated for-profit entities with an ownership structure that allows equity financing.

Next to equity and debt funding, MFIs use structured finance to fund their loan portfolios (Byström, 2008). Structured finance is based on the process of securitization, which transforms an MFI's loan portfolios in separate classes of securities or tranches with different risk-return profiles. When some MFI borrowers default, the holders of the most senior tranches are paid first, next the junior tranches are paid, and finally the equity tranche holder are paid the remainder. By opting for the most senior tranches investors who would find microfinance investment otherwise too risky can also invest in microfinance. In addition, structured finance products can contain the loan portfolios of many MFIs, so it allows investors to diversify across different MFIs by investing in a single product.

To some extent the popularity of microfinance investment stems from the increased popularity of socially responsible investment. In addition, investor's interest is driven by the increased profitability of institutions created by the drive towards commercialization. The fact that many of the world's poor are still unbanked makes commercial microfinance a large potential growth market.

## 1.4 Is microfinance good for the poor?

But what is good for investors is not necessarily good for the poor. To measure the success of microfinance, research has used different units of analysis. Table 1.1 provides a general typology of these units of analysis, where the columns indicate the unit of analysis and the rows the perspective. Because microfinance is first and foremost a development tool, most microfinance research has focused on the poor customer as unit of analysis. These studies increase our understanding of credit

Table 1.1. A general typology of microfinance studies

	Poor customers	Microfinance institutions (MFIs)	Investors and donors
Financial perspective	Optimal microfinance contracts	MFI financial performance, efficiency and risk (chapter 4, 5 and 6)	Microfinance investments funds (chapter 3)
Social perspective	Impact studies	MFI outreach (chapter 4)	Donor funding

markets in developing countries and test whether microfinance has a measurable impact on improving the lives of the poor. Yet, with the process of commercialization MFIs professionalized and to allow them to attract donors and social investors they increasingly made their financial and social performance data available. At the same time, the research community took an interest in analyzing the role of MFIs in providing financial services to the poor. Finally, investors and donors have received relatively little interest in the literature, because data on MFI investments and donations is limited.

Taking a financial perspective, there is a body of literature that discusses optimal microfinance contracts. Theoretical work in this area tries to explain how innovations, like group liability, dynamic incentives, repayment frequency and social capital lower the administrative costs of making small loans (e.g. Chowdhury, 2007; Ghatak and Guinnane, 1999; Gangopadhyay et al. 2005). Recently, the research community has started to test these theories using randomized control experiments. For instance, Karlan and Zinman (2009) test dynamic incentives by promoting randomly chosen borrowers a lower future lending rate conditional on repayment and Gine and Karlan (2009) test group liability by randomizing individual and group liability. According to Banerjee and Duflo (2010) the interplay between theory and experiments is very productive, as theory motivates experiments to test the theory, the results of which can be used to further refine theory.

Impact studies take the social perspective and investigate whether microfinance measurably improves the lives of the poor. The earlier studies in this area were non-experimental, which raised well-known problems of reverse causality. Nonetheless, two well-known studies (Pitt and Khandker, 1998; Khandker, 2005) make strong claims to causal identification. They find that microfinance reduces poverty and is especially effective for female borrowers and the extremely poor. Yet, Morduch (1998) and Roodman and Morduch (2009) have been very critical of

these findings. In revisiting the analyses of Pitt and Khandker (1998) and Khandker (2005) they conclude that survey data cannot offer decisive evidence in favor of the impact of microfinance.

In response to the identification problems associated with analyzing household survey data, many impact analyses now use randomized trials. The results of the first randomized impact studies are mixed. Banerjee et al. (2010) find that borrowers that want to start a new business increase their durable consumption at the expense of nondurable consumption, but households that do not intend to start a business increase their nondurable consumption instead. In addition, they find no impact of microfinance on health, education or women's decision-making. Karlan and Zinman (2010a) find that consumer credit improves most poor borrower outcomes. Yet, Karlan and Zinman (2010b) find that businesses actually shrink when they obtain microcredit and access to credit only increases profits for male but not for female entrepreneurs. So the effects are heterogeneous: microfinance does not necessarily attack poverty by helping female borrowers start and grow a small business. Instead, the effects of microfinance are very context-specific, because each study investigates a different MFI that operates in a different country and offers a different product. We have to wait until we know the results of the additional randomized impact studies that are now underway, before we can start to draw any general conclusions.

## 1.5 Why invest in microfinance?

Due to limited data availability, most studies on microfinance investment still use MFI data instead of investment or donation data. For instance, Cull et al. (2009) show that there are large differences between types of MFIs in how they obtain funding. Banks rely mostly on deposits (71%), followed by equity and commercial borrowing (both 13%). On the other side of the commercial spectrum, nongovernmental organizations (NGOs) rely mostly on donations (39%), followed by commercial borrowing (26%) and noncommercial (soft) loans (16%). So NGOs still rely very much on subsidies: for the median NGO the subsidy per borrower is \$233 (in purchasing power parity equivalents). Still, they rely for 42% on debt investments, so investors can invest in NGOs through funds that invest in NGO debt.

Diversification is often given as motivation to invest in microfinance. As global capital markets become more integrated also emerging markets become more correlated with developed markets. Therefore, international investors continually look

towards new, or frontier, emerging markets to better diversify their portfolio. Microfinance investment is often suggested as alternative, because MFIs lend to customers that operate in the informal sector, which is less sensitive to macroeconomic cycles.

The literature finds mixed evidence on the correlation of microfinance with macroeconomic events. Ahlin and Lin (2006) find that the macroeconomic environment is a significant determinant of MFI performance, but Gonzalez (2007) finds only limited evidence for a correlation between microfinance and the macroeconomy. Kraus and Walter (2010) examine whether microfinance is low correlated with international and domestic market performance. Their analysis shows that MFIs are not correlated with global markets, whereas MFI performance is significantly correlated to the domestic macroeconomy. This suggests that microfinance investment is especially interesting for international investors.

The papers that look at the correlations between microfinance and other assets do not allow us to directly assess whether microfinance investment improves the diversification of investment portfolios. In chapter 3 we test whether the mean-variance frontier shift outwards when adding microfinance to an investment portfolio of international assets using a mean-variance spanning test (De Roon et al., 2001). This provides a direct test of the diversification advantages of microfinance, which can be directly compared to De Roon et al. (2001) who find no diversification advantages of investing in emerging market indexes.<sup>2</sup>

As another motivation to invest in microfinance, many mention the high repayment rates—sometimes above 95%—which suggests that a microfinance investment could be very profitable. Still, serving the very poor is costly because their loans are relatively small compared to the cost of administering them. Because the microfinance sector is much more commercialized in Latin America—where there are many for-profit institutions—than in Africa, which has mostly non-profit MFIs, chapter 3 makes a distinction between the different MFI types and regions.

## 1.6 Trade-off between financial and social objectives

In studying the MFI, authors investigate financial indicators, social indicators or both. Many studies take a cross-country perspective using data provided by Mix-Market ([www.mixmarket.com](http://www.mixmarket.com)). One of the first and most well-known studies in

---

<sup>2</sup>Note that the results of De Roon et al., 2001 apply only when there are short sales restrictions. We also apply short sales restrictions in our tests in chapter 3

this tradition is Cull et al. (2007), who investigate both financial and social MFI indicators and conclude that there is a trade-off between financial and social performance. Also Hermes et al. (2011) find evidence of this trade-off in a stochastic frontier analysis. This trade-off implies that an MFI's commercialization decreases its ability to help the poorest of the poor. Consistently, Cull et al. (2009) show that nonprofit MFIs still serve the poorest of the poor, while for-profit institutions serve the somewhat less poor.

When socially responsible investors have decided to invest in microfinance, they face a trade-off between financial returns and outreach to the poor (Cull et al., 2009; Hermes et al. 2011). Even very poor lenders often have very high repayment rates, so repayment rates do not drive the trade-off. Instead, the higher operating costs of small loans versus large loans are likely to drive the trade-off. For instance, it is more costly to administer and monitor a 1000 loans of \$200 than doing the same for a single loan of \$200,000.

In chapter 4 we ask whether, next to the trade-off between financial returns and outreach, there is also a trade of between outreach and risk. The high repayment rates of very poor lenders suggest there is none. Still, MFIs that serve the poorest of the poor are usually NGOs that could be more risky because: First, they depend on subsidies. Second, they are typically smaller such that they have less deep pockets to overcome setbacks. Third, they are usually not allowed to take deposits such that they are more exposed to refinancing risk. Fourth, they are typically not regulated by a central bank. In chapter 4 we try to find some suggestive evidence that supports these claims.

Next, we try to quantify the trade-off between financial returns, risk and outreach to the poor. In finance the trade-off between risk and return is well known from the mean-variance framework of Markowitz (1958). In chapter 4 we adapt this framework to also include the trade-off between return and outreach and the trade-off between risk and outreach. The goal of this exercise is to attach a price to outreach, such that socially responsible investors know how much return they have to give up or how much extra risk they are willing to bear to obtain a portfolio with more outreach to the poor.

## 1.7 Microfinance risks

MFIs face many risks that endanger their long-term sustainability. Microfinance investors also face many of these risks. As we explained above, microfinance is

Table 1.2. Risk types

Financial risks	Operational risks	Strategic risks
Credit risk	Transaction risk	Governance risk
Liquidity risk	Fraud (Integrity) risk	Reputation risk
Market risk	Legal & compliance risk	External business risk

Adapted from GTZ (2000)

often presented as a relatively low risk investment; repayment rates are high and microfinance returns are low correlated with macroeconomic events. Yet, the crisis that started taking hold in 2008 has shown that also microfinance is not immune to macroeconomic events. The financial crisis made it more difficult for MFIs to obtain funding, especially when they did not collect savings. Moreover, the commercialization of microfinance has fueled competition between MFIs and commercial banks. This has led to an erosion of lending standards, which now increases the fear for overindebtedness.

If anything, the financial crisis has shown that MFIs are subject to the risks common to all financial institutions, most of which can be categorized into three general categories shown in Table 1.2: financial, operational and strategic risks (GTZ, 2010). First, financial risks include credit, liquidity and market risk. Credit risk is the risk to earnings or capital due to borrowers' late and non-payment of loan obligations. Much of the initial success of microfinance is due to the development of lending policies that limit the credit risk due to lenders' lack of collateral. Credit risk is closely related to liquidity risk, which is the risk that an MFI cannot meet its current cash obligations. For example, a loan default is both a credit risk and a loss of liquidity. Two important market risks are interest rate risk and foreign currency risk, which are the risks due to fluctuations in interest rates and currency values, respectively. Microfinance investors typically transfer their currency risk to the MFIs they lend to. Most MFIs borrow in US dollars and lend in local currency. In the event of a sudden appreciation of the dollar against the local currency, MFIs experience a loss.

Second, operational risks are the risks arising from the daily operation of the MFI through people, systems and processes. It is a very broad concept that can include many types of risks. There are two risks in this category to which MFIs are particularly susceptible, namely transaction risk and fraud risk. Transaction risk is high for MFIs because they handle a high volume of small transactions daily. Loans are small and transaction costs are already large, so crosschecking is not cost-

effective. The most common type of fraud risk is the direct theft of funds by loan officers. Again, this is costly to control because it involves other officers than the loan officer to visit clients and verify their account balances.

Third, strategic risks include internal risks due to bad business decisions, poor leadership and governance, but also external risks MFIs face in their environment. A typical strategic risk is governance risk, which is the risk of having an inadequate structure or body to make effective decisions. An example of governance risk is reputation risk, which is the risk arising from the effects of negative publicity. Especially commercializing MFIs are subject to reputation risk: the case of Compartamos shows that more commercialization could create a backlash against microfinance, threatening future funding by socially responsible investors.

In chapter 5 we investigate the governance risk emanating from the board's composition. Many empirical MFI analyses focus explicitly on governance issues. This focus is warranted because MFIs face complicated governance issues. Of special interest is the question whether microfinance's dual objective of financial sustainability and outreach to the poor can be achieved using standard governance mechanisms. Labie (2001) explores this question conceptually by indicating the special governance needs in microfinance. Hartarska (2005) provides empirical evidence. She studies the governance of MFIs from Central and Eastern Europe and finds that performance-based compensation of managers is not associated with better-performing MFIs. To some extent the proliferation of governance studies has been fueled by data availability. Many empirical studies on this topic use the dataset of Roy Mersland with governance data obtained from rating agencies (e.g. Mersland, 2009; Mersland and Strøm, 2009; Mersland and Hartarska, forthcoming). Whereas the MixMarket dataset we use in all other microfinance chapters does not include information on governance arrangements, Mersland's dataset does. In chapter 5 we use this dataset to investigate the relation between governance arrangements and MFI risk.

Excessive MFI risk-taking is an outcome of the board decision-making process, which means the composition of the board plays a key role. To understand the impact of board decision-making on MFI risk, Adams and colleagues (2005) theorize that in a firm in which the CEO makes most relevant decisions (a firm with a powerful CEO), outcomes are more extreme than they would have been if the firm relied on a consensus among all board members to make decisions. The degree of freedom managers have in decision-making is influenced by factors like the type of firm and the market in which they operate. Based on Adams and colleagues

(2005) we provide a typology of MFI types, which we use to argue that less commercialized MFIs give managers more decision-making freedom. So we predict that powerful CEOs can make the most extreme decisions in non-profit MFIs (Non-governmental organizations), such that non-profit MFIs with powerful CEOs have the most variable performance.

Still, the effect of CEO power on variability is not necessarily bad as long as CEO power is associated with large positive deviations from the mean. It is only bad when CEO power leads to extremely bad decisions and thus large negative deviations from the mean. Therefore, we also investigate whether CEO power is related to the positive or the negative deviations from expected performance using quantile regression.

In chapter 6 we focus more on the MFI's external risks. As MFIs commercialize to become formal financial institutions, they are more influenced by the financial economy and thus become more exposed to external risks like competition and financial crises. In addition, formal institutions are subject to more regulation, which creates the risk of not conforming to a country's laws and regulations: regulatory risk.

Also a lack of enforcement of regulations can be a risk for financial institutions. Especially in developing countries debt enforcement institutions are very weak. While in developed countries it takes usually less than a year to resolve insolvency, in poor countries it often takes more than five years to resolve insolvency (Djankov et al., 2008). In case of insolvency, waiting five years to retrieve the collateral implies that lenders are much less willing to provide credit, which is also found by Djankov et al. (2007). In chapter 6 we argue that in developing countries microfinance could be a more efficient instrument than formal finance, because microfinance contracts do not require any collateral. Therefore, microfinance institutions have a competitive advantage vis-à-vis regular financial institutions when contract enforcement is weak. A larger market for microfinance, with more diverse customers, implies more diversification opportunities for MFIs' loan portfolios. Therefore, we hypothesize that weak contract enforcement is associated with less MFI risk.

## 1.8 Summary

The commercialization of microfinance has connected the world of microfinance, which was previously primarily donor dominated, with the world of socially responsible investment. In chapter 2 we try to find out whether the popularity of

socially responsible investment affects stock prices and returns. Chapter 3 investigates whether microfinance investors obtain diversification benefits from their investment. Chapter 4 investigates whether there is a risk-return-outreach trade-off and tries to quantify this trade-off. Chapter 5 and 6 look at microfinance governance risk and regulatory risk, respectively.



## *Chapter 2*

# The stocks at stake: return and risk in socially responsible investment

## 2.1 Introduction

Socially responsible investing (SRI) attracts a lot of investor attention. According to the Social Investment Forum ([www.socialinvest.org](http://www.socialinvest.org)), approximately 10% of investments are managed according to some screening process related to SRI. In addition to financial performance, social investors are concerned about non-financial dimensions of corporate performance, such as the impact on the environment, social relations, and corporate governance. This multi-dimensional nature of corporate performance raises the question whether a trade-off exists between the financial dimensions of performance and the non-financial dimensions. Most empirical studies suggest no trade-off since there is little difference between the (risk-adjusted) returns of stocks satisfying SRI criteria (for an overview, see Renneboog et al., 2008). However, Hong and Kacperczyk (2009) report higher expected returns for stocks that are excluded from a portfolio because of negative ethical issues (companies producing alcohol, tobacco, and gaming).

Theoretical work on the relationship between SRI and expected returns focuses on the discrepancies in prices that are the result of demand differences for different types of stocks. The demand differences can either be due to incomplete in-

formation (Merton, 1987), (green) investor preferences (Heinkel et al., 2001) or the internalization of externalities (Dam, 2008). These explanations all share a basic feature, namely that excess demand for socially responsible stocks and a shortage of demand for irresponsible stocks will lead to overpricing of the first and underpricing of the latter. The shortage of demand for irresponsible firms' stock implies that the risk sharing opportunities for people investing in these stocks are limited and therefore command a return premium (Merton, 1987). In a neo-classical equilibrium model, Dam (2008) shows that even when we assume equal risk levels for responsible and irresponsible firms, socially responsible firms will have both lower returns and lower book-to-market ratios than their irresponsible industry peers. In contrast, the empirical literature on SRI does not conclude that responsibility is priced by the capital markets (Renneboog et al., 2008).

We study the contradiction between the results found in the empirical literature and the predictions from the theoretical models. In our view, it is the result of a misinterpretation of the risk-adjusted performance measures used in most empirical studies. This misinterpretation arises from two possible errors. The first error is that financial performance is calculated by controlling for systematic risk, whereas the empirical measure of systematic risk captures part of the trade-off. The second error is that aggregate measures of SRI may confound existing relationships between individual dimensions of SRI and returns.

The first error is related to the use of regression models including risk factors such as those suggested by Fama and French (1992). In these, the intercept is usually interpreted as a measure of risk-adjusted performance. An intercept not significantly different from zero is usually interpreted as evidence that the assets are priced according to a rational asset pricing model. However, SRI and non-SRI firms with equal risk levels may have different book-to-market ratios due to an excess demand for SRI stocks. In the context of the model of Fama and French (1992), this implies that the exposure to the factor reflecting the influence of the book-to-market factor is independent of the risk profile of the underlying cash flows. As a result, the trade-off between financial and SRI performance is at least partly captured by the book-to-market ratio.

The second error relates to the use of aggregate measures of SRI. One of the reasons why the empirical literature yields few significant relations between SRI and expected returns may be due to the aggregation over different dimensions that have confounding effects. For example, it is possible that positive news on environmental friendly production is positively related to expected returns, whereas news

pertaining to good employee relations is negatively related. Therefore, we investigate different dimensions of responsibility.

We will first analyze the risk-adjusted performance in a way that is consistent with the existing literature. To test the return implications of SRI, we form portfolios based on positive scores on the strength and concern screens of six SRI dimensions on the universe of stocks tracked by KLD Research & Analytics, Inc. during the period 1992 to 2006. We test whether each of these portfolios can deliver excess returns by estimating the Fama-French (1993) asset pricing model augmented with the Carhart (1997) momentum factor in a system GMM framework. Our results confirm earlier findings that the risk-adjusted performance of SRI stocks is not significantly different from zero. We take a closer look at the impact of SRI scores on excess returns by regressing these returns on lagged SRI scores for our six dimensions using Fama-MacBeth (1973) regressions. Next, we analyze the book-to-market ratio and find it is affected by some individual SRI scores. In particular, Diversity and Environment have a negative relationship with the book-to-market ratio whereas Governance has a positive relationship. Therefore, we conclude that SRI impacts on stock returns by lowering the book-to-market ratio and not by generating positive alphas in a linear regression model. This result is consistent with the theoretical work suggesting that SRI is reflected in demand differences between SRI and non-SRI stock. It also explains why so few studies do find a relationship between alphas and SRI investing.

This chapter is structured as follows. In section 2 we briefly discuss the literature on the relation between stock returns and SRI. In section 3, we discuss the data and the methodology. In section 4 we discuss the empirical results. Finally, section 5 concludes.

## 2.2 Background

Kurtz (1997) and Bauer et al. (2005) establish that socially responsible stocks do not appear to underperform the market as a whole (see Renneboog et al., 2008, for an overview of the literature). However, Kempf and Osthoff (2007) report positive and significant risk-adjusted returns during 1992-2004 for a US portfolio based on a sample of SRI stocks from the KLD database. Their portfolio is based on a long-short strategy by investing in the 10% best SRI stocks within each industry and shorting the 10% worst SRI stocks within each industry. In contrast, Hong and Kacperczyk (2009) report higher expected returns for stocks that are usually

excluded from a portfolio because of negative ethical issues. For example, they exclude companies involved in alcohol, tobacco, and gaming. They find that these so-called sin stocks are underpriced, have higher book-to-market values, and higher excess returns than other stocks. In addition, they find that sin stocks have less analyst coverage and are less held by pension funds.

Most formal theoretical work on the relationship between SRI and expected returns is reminiscent of Merton (1987). Merton (1987) focuses on the discrepancies in prices that are the result of incomplete information in the sense that individual investors do not have information about all securities regarding expected return, variance, and covariance with other securities. Investors do not include securities in their portfolio for which they lack such information. Merton (1987) shows that in the presence of this type of incomplete information, firm size, firm-specific return variance and the fraction of investors that know about a security all impact on risk-adjusted returns. This model can also be used to analyze the impact of self-imposed restrictions on investment portfolios by considering the stocks that should be excluded from the portfolio based on some a priori criterion as stocks with lacking information (see also Białkowski et al., 2008). Thus, in the context of SRI, the increased (or decreased) risk of a firm acting in a socially responsible manner could increase (or decrease) its expected return. Other theoretical models are based on differences in investor preferences regarding non-financial performance characteristics. For example, in Heinkel et al. (2001), investors differ with respect to their preference for green companies. Fama and French (2007) refer to differences in preference for any non-financial performance characteristic. Dam (2008) models investors as differing in tastes and firms as differing in their policies of internalizing externalities. These models all share one basic feature, namely that excess demand for socially responsible stocks and a shortage of demand for irresponsible stocks will lead to overpricing of the first and underpricing of the latter. The shortage of demand for irresponsible firms' stock implies that the risk sharing opportunities for people investing in these stocks are limited and therefore command a return premium.

## 2.3 Data & Method

### 2.3.1 Data

We obtain data on social responsibility from KLD Research & Analytics, Inc. and financial performance measures from Datastream. Other researchers have used

these databases too when investigating the relationship between financial performance and SRI (e.g. Hillman and Keim, 2001; Kempf and Osthoff, 2007). KLD uses screens to monitor SRI and it has expanded its universe of coverage over the last couple of years. In the 1990s, it covered the S&P500 Index and the Domini 400 Social Index. In 2001 the database was extended to include all constituents of the Russell 1000. In 2003 the database was further extended to include all stocks from the Russell 2000 as well. KLD does not have historical ratings data for non-US companies, unless it is a member of the S&P500. In our study, we will include all stocks covered by KLD.

KLD uses multiple criteria on which firms are evaluated, using both positive and negative screens. Positive screens indicate strengths and negative screens indicate weaknesses of the firm. Each screen is a binary variable that reflects whether the firm meets the particular criterion. These screens are renewed at the end of each calendar year. The screens are summarized in groups of corresponding items referring to a general theme. In the period under review, KLD identifies six themes: Community involvement, corporate governance, diversity, employee relations, environment, and product (see [www.kld.com](http://www.kld.com) for detailed information about the themes and their strengths and weaknesses). The first relates to how the firm interacts with its social environment. Corporate governance relates to how the firm is governed and directed. Diversity is about the composition of the workforce, especially senior management and the board. Employee relations are about the relationship between the company and its employees and in particular concerns issues related to employee compensation. Environment is about environmental management and policies. Finally, product is about strengths and weaknesses in relation to the quality of the products and production processes of the firm. Apart from these six themes, KLD also investigates companies' behavior with respect to human rights. However, as this is undertaken since 2000 only, we do not include this item in the analysis because it substantially reduces the number of observations in our analysis. Furthermore, KLD has exclusionary screens for alcohol, gambling, firearms, military, nuclear power, and tobacco. Given the nature of these screens, namely focusing only on concerns, it is excluded from our analysis.

Return and accounting data were obtained from Datastream. This includes monthly data on returns, market values, company age, R&D expenditures, net sales, book equity, number of shares outstanding, and net income. The time period covered for these data is June 1992 to July 2006 for our monthly portfolio and Fama-MacBeth (1973) regressions and December 1991 to December 2004 for our yearly

market-to-book regressions. Monthly data is measured at the end of each calendar month and yearly data at the end of each calendar year. The return and accounting data were linked with the KLD data based on ticker and name for the oldest data and on CUSIP code for the more recent data. Finally, the independent variables used in our portfolio regressions, the value-weighted market proxy, the SMB, HML and MOM factors and the risk free rate, were obtained from Kenneth French's website.

To assess the effect of KLD scores about corporate social responsibility on financial performance, we perform three types of analysis. First, we use these scores to form portfolios and assess their performance. Second, we perform a series of Fama-Macbeth (1973) regressions to test the direct effect of KLD scores on excess returns. Finally, we look into the impact of the scores on firm value by means of pooled book-to-market regressions.

### 2.3.2 SRI Portfolios

Twelve portfolios are formed for the six SRI dimensions based on whether stocks score on the particular strength or concern screen. KLD assigns CSR ratings at the end of each year. To be certain that the social responsibility and financial information for year  $t - 1$  is known, we calculate returns on monthly equally weighted portfolios beginning in July of year  $t$  to June of year  $t + 1$ . Equally weighted portfolios are rebalanced at the beginning of July each year. Portfolios that capture the positive and negative dimension of a certain screen are not mutually exclusive as a portfolio can obtain a positive score on both (see also Driessen and Laeven, 2007, and Chua et al., 2008). The monthly excess returns of the portfolios are assessed using the Fama and French (1993) three-factor model expanded with the Carhart (1997) momentum factor:

$$R_{i,t} - RF_t = \alpha_i + \beta_i(RM_t - RF_t) + s_iSMB_t + h_iHML_t + m_iMOM_t \quad (2.1)$$

where  $R_{i,t}$  is the return on portfolio  $i$ , constructed as explained above,  $RM_t$  is the return in month  $t$  on a value-weighted market proxy,  $RF_t$  is the return in month  $t$  of a one-month treasury bill,  $SMB_t$  is the difference in monthly return between a small and large-cap portfolio,  $HML_t$  is the difference in return between a value and a growth portfolio, and  $MOM_t$  is the monthly return on a portfolio long on past one-year winners and short on past one-year losers. The momentum factor is designed to capture the risk due to the momentum found in stock returns by

Jegadeesh and Titman (1993). Summary statistics on the portfolios and factors are reported in panel A of Table 2.1. In addition to testing the returns on the individual portfolios, we also test the return on a differenced portfolio (see Derwall et al., 2005):

$$R_{t,i,s} - R_{t,i,c} = \alpha_i + \beta_i(RM_t - RF_t) + s_iSMB_t + h_iHML_t + m_iMOM_t \quad (2.2)$$

where  $R_{t,i,s}$  is the return on one of the six strength portfolios and  $R_{t,i,c}$  is the return on its accompanying concern portfolio. The independent variables are similar to those in (2.2), except for  $\alpha_i$ , which is now the differential excess performance.

The set of portfolio equations is tested in a GMM system as in MacKinlay and Richardson (1991) and Clare et al. (1997). This estimation allows the errors of equations to be correlated. Given the fact that our portfolios are all correlated with a correlation coefficient of .80 or higher, estimating a system is more efficient. Estimating the portfolios in a GMM system as opposed to OLS or SUR also has the advantage of being able to rely on weaker assumptions. In particular, GMM does not rely on the assumption of homoskedasticity and normality of returns. The estimation procedure is to construct a series of errors from equation system 1 so that they are orthogonal to a vector of instruments for all equations. Given the fact that we do not include any conditional information, these instruments consist of a constant and our independent variables. The GMM procedure then chooses parameters  $B_0 = [\alpha, \beta, s, h, m]$  that set particular linear combinations of the moment conditions to zero. We define  $x_t = [1, (MKT_t - RF_t)', SMB_t', HML_t', MOM_t']$  and  $\epsilon_t = R_t - Bx_t$ . The moment conditions used by the GMM estimation of B are:

$$E[g_t] = E[x_t \otimes \epsilon] = 0 \quad (2.3)$$

Since the system is exactly identified, the estimate of B does not depend on the weighting matrix and remains the same as the OLS estimate of the system (Hansen, 1982). However, when there are more restrictions than parameters, the system is overidentified and the moment conditions can no longer be zero for any choice of parameters. In that case, the GMM estimator is identified by minimizing such that is as close to zero as possible. As in Clare et al. (1997), we use a two-stage GMM approach for which we report adjusted t-statistics to take account of small sample bias (Ferson & Foerster, 1994). The adjustment factor with which we multiply the asymptotic variance is  $T/(T - P)$ , where  $T$  is the number of time series observations and  $P$  is the number of model parameters. To test whether coefficients

Table 2.1. Summary Statistics

Panel A: Summary statistics equally weighted SRI portfolios		
Variable	Mean return (in %)	Standard deviation (in %)
<i>SRI Portfolios</i>		
Community strengths	1.29	3.76
Community concerns	1.24	4.52
Diversity strengths	1.27	4.30
Diversity concerns	1.18	4.91
Employee relations strengths	1.25	4.48
Employee relations concerns	1.26	5.00
Environment strengths	1.16	4.12
Environment concerns	1.16	4.24
Product strengths		4.47
Product concerns		4.05
Governance strengths	1.27	4.49
Governance concerns	1.27	4.70
<i>SRI Difference Portfolios</i>		
Community	0.05	1.85
Diversity	0.09	1.74
Employee relations	0.00	1.24
Environment	0.00	1.15
Product	0.04	1.97
Governance	0.00	2.25
<i>Portfolios used in Fama and French regressions</i>		
Market portfolio	0.64	4.13
SMB portfolio	0.26	3.83
HML portfolio	0.46	3.53
MOM portfolio	0.91	4.99

Notes: This table presents the summary statistics for the returns used in each of the three different analyses. It consists of panel A, B and C. Panel A presents the statistics for the data used in the performance assessment of the portfolios based on individual KLD criteria. First we present the mean and standard deviation of time series returns for portfolios constructed on the basis of different SRI criteria. The SRI difference portfolios represent the time series of differences in return of a portfolio consisting of stocks that score positively on a particular screen and the return of a portfolio consisting of stocks that score negatively. Finally, we present the mean and standard deviation of the time series of returns of the Fama and French factors used in the analysis.

are zero across the system, we use a J-test of overidentifying restrictions (Hansen, 1982). Since we have six instruments for each equation, (2.1) and (2.2) generate 72 and 36 orthogonality conditions, respectively. However, restricting one of the coef-

Panel B: Summary statistics of variables used in Fama-MacBeth Regressions

Variable	Time-Series Average of Means	Time-Series Average of Standard Deviations
Excess return (%)	0.959	10.154
Beta	0.965	0.400
Log(Size) ( $\times 1,000$ )	7.910	1.583
Past 12 month returns (%)	1.260	10.156
Turnover (%)	0.566	0.903
Log(B/M)	-0.927	0.704
Log(Age)	3.093	0.504

Notes: This panel reports summary statistics on the variables used in the cross-sectional regressions. The summary statistics of the SRI variables are reported in Panel C. Excess return is a stocks monthly return net of the risk free rate. Beta is a stocks post-ranking Beta calculated following Black et al. (1972). Log(Size) is the logarithm of company market capitalization at the end of month  $t - 1$ . Log (B/M) is the logarithm of the book-to-market ratio at the end of month  $t - 1$ . Return is the simple average of returns during the past 12 months, lagged one month. Turnover is the 1 month lagged monthly average of daily share turnover, which is calculated as average shares traded divided by shares outstanding during month  $t$ . Log(Age) is the logarithm of company age measured at the end of the previous year.

ficients to be zero across the system implies that the number of parameters to be estimated is restricted to 60 and 30, respectively. So the system is overidentified. Therefore, we also report J-statistics for iterated GMM estimates since Ferson and Foerster (1994) show that these are more reliable.

### 2.3.3 Fama-MacBeth regressions

In the previous section, we used portfolios to establish the relationship between risk and returns for groups of stocks satisfying specific SRI criteria. Here, in order to establish the relationship between returns and SRI at the level of individual stocks, we use cross-sectional regressions because we are interested in assessing the direct impact of KLD scores on excess returns. This allows us to identify whether aggregation over different dimensions have confounding effects in identifying the relation between SRI and return. Using the SRI scores defined above along with a host of control variables, we estimate the following regression:

$$R_{i,t} - RF_t = \alpha_i + \beta_1 \mathbf{SRI}_{t-1} + \beta_2 \text{Beta}_{i,t} + \beta_3 \mathbf{X}_{i,t-1} + \epsilon_{i,t} \quad (2.4)$$

where  $R_{i,t}$  is the monthly return of stock  $i$  in month  $t$  and the risk free rate is as defined above. The vector  $\mathbf{SRI}_{t-1}$  includes the scores of the six SRI variables as

Panel C: Summary statistics of variables used in market-to-book regressions

Variable	Time-Series Average of Means	Time-Series Average of Standard Deviations
Log(B/M)	-0.958	0.693
Community	0.277	0.658
Diversity	0.385	1.083
Employee Relations	0.123	0.822
Environment	-0.139	0.838
Product	-0.127	0.695
Governance	-0.258	0.621
ROE	0.112	0.250
R&D/Sales	0.062	0.846
R&Dmissing	0.607	0.488
Log(Age)	2.730	0.661
Community strengths	0.335	0.634
Community concerns	0.057	0.228
Diversity strengths	0.603	0.954
Diversity concerns	0.218	0.401
Employee relations strengths	0.403	0.641
Employee relations concerns	0.280	0.516
Environment strengths	0.240	0.491
Environment concerns	0.379	0.819
Product strengths	0.150	0.368
Product concerns	0.278	0.590
Governance strengths	0.088	0.284
Governance concerns	0.346	0.524

Notes: All variables are measured at the end of the year. Log(B/M) is the logarithm of book-to-market value. The SRI variables community, diversity, employee relations, environment, product and governance are computed as the sum of all strengths minus the sum of all concern scores within each dimension. R&D Sales is the fraction of sales spent on R&D expenditures in year  $t$ . R&D missing is a dummy that is one when the variable R&D/Sales is missing and zero otherwise. Log(Age) is the logarithm of age based on the base date in Datastream and measured at the end of each year. ROE is the return on equity of firm  $i$  in year  $t$  winsorized to exclude the 0.5% smallest and largest observations.

in the cross-section regressions, but this time measured at the end of year  $t$ .  $Beta_{i,t}$  is a stock's post-ranking beta estimated using the traditional method of Black et al. (1972).  $X_{i,t-1}$  is a vector of control variables similar to those used by Hong and Kacperczyk (2009), including the natural logarithm of firm  $i$ 's market capitalization at the end of month  $t - 1$ , the logarithm of the book-to-market ratio of stock  $i$  at the end of month  $t - 1$ , a firm's simple average of returns during the past 12 months, the

one-month lagged monthly average of daily share turnover in stock  $i$ , the natural log of a company's age measured at the end of month  $t$ , and a dummy that is equal to one if a stock belongs to the Russell 1000 or 2000 index but not to the S&P 500. This dummy captures any effects that are due to the enlargement of the number of stocks covered by KLD.

### 2.3.4 Book-to-market regressions

Thirdly, we investigate the impact of KLD scores on the value of the firm by using pooled book-to-market regressions. To this extent, we regress a firm's book-to-market ratio on a set of well-known predictors of book-to-market ratios and the KLD scores we also used in the cross-section regressions. The KLD scores are formed on six dimensions adding a point when a stock scores positively on a dimension's strength screen and subtracting a point when a stock scores negatively on a dimension's strength screen. The most elaborate specification we test is the following:

$$\log(B_{i,t}/M_{i,t}) = c_0 + c_1SRI_{i,t} + c_2X_{i,t} + \epsilon_{i,t} \quad (2.5)$$

where  $\log(B_{i,t}/M_{i,t})$  is the logarithm of the book-to-market ratio of stock  $i$  at the end of year  $t$ .  $SRI_{i,t}$  is a vector containing the (lagged) scores of the six SRI variables; Community, corporate governance, diversity, environment, employee relations and product. The vector  $X_{i,t}$  includes several control variables known to correlate with the book-to-market. It includes the fraction of sales spent on R&D expenditures in year  $t$ , a dummy that is one when the fraction of sales spent on R&D is missing, and a dummy for stocks belonging to the Russell 1000 or 2000, but not the S&P500. Furthermore, we included the logarithm of age as measured at the end of each year. Finally, ROE is the return on equity winsorized to exclude the 0.5% smallest and largest observations. Summary statistics are in panel B of Table 2.1.

In estimating (2.5), we do not use Fama-Macbeth (1973) regressions but pooled OLS with robust standard errors. This is because the Fama-Macbeth approach to estimating panel data is useful in adjusting for correlation in the cross-section, but understates standard errors when the dependent variable is correlated across time (Bali et al., 2008; Petersen, 2009). Return data only suffer from minor autocorrelation. However book-to-market ratios are very much correlated across time and in the cross-section. Therefore, we cluster standard errors both by firm and by time (see Thompson, 2011). However, these standard errors are only asymptotic-

ally correct. For the standard errors clustered by firm this poses no problem, but for standard errors clustered by time it does since we only have 14 years of data. Therefore, we also report a second specification in which we adjust for autocorrelation by including time dummies.

## 2.4 Results

### 2.4.1 SRI portfolios

In Table 2.2 we present the results of the Fama and French regressions on the portfolios screened for different SRI characteristics. From panel B we see that none of our SRI portfolios shows significant outperformance, although we should note that the adjustment factor is largely responsible for this result. The necessity of adjusting for a large number of factors and equations can also be seen by comparing the two J-statistics that test whether a coefficient is zero across all equations. J-statistic A was computed using 2-stage GMM, whereas J-statistic B was computed using iterated GMM. Following J-statistic A, we should reject the hypothesis of zero alpha across all equations at the 5% level, whereas following J-statistic B we would not be able to reject this hypothesis. Although we know from Ferson and Foerster (1994) that iterated GMM has somewhat lower power than 2-stage GMM, the difference in p-values is large enough to suspect that 2-stage GMM leads to overrejection.

Looking at the difference between SRI strength and concern portfolios has the advantage of reducing the dimensionality of the system, next to being able to assess the difference in factor exposure and performance between strength and concern portfolios. Concerning the first, the difference in p-values of the J-statistics is much smaller so that using different estimation methods does not lead to qualitatively different results. The results in panel A clearly show that there are significant differences between the strength and the concerns portfolios. We find that for four out of six portfolios, the strength portfolio has a significant lower exposure to the HML factor than its accompanying concern portfolio, suggesting that these strength portfolios are more growth oriented than their concern counterparts. Finally, only the community strength portfolio significantly outperforms its accompanying concern portfolio. The excess return associated with this portfolio is 3.4% (significant at the 10% level). The fact that CSR strength portfolios have lower book-to-market ratios than their concern counterparts is consistent with overpricing. However, overpricing of CSR strength stocks vis-à-vis concern stocks also implies that CSR strength portfolios should have lower performance than concern portfolios, which is clearly

not the case and even opposite for the community difference portfolio. To further investigate the pricing impact of SRI scores, we perform book-to-market regressions.

## 2.4.2 Fama-MacBeth regressions

Looking at the results in Table 2.3, we observe that beta and turnover are not significant and that book-to-market and age have a negative effect on subsequent returns. Although size and past returns do not have a significant influence, they do have the expected signs. Concerning the SRI scores, we see that only the employee relations score has a significant positive effect on excess returns. Although it is only significant at the 10% level, the result is robust to the inclusion of numerous control variables, including 39 industry dummies. In fact, the effect of most controls is consistent with those in Hong and Kacperczyk (2009). The outperformance of about 0.07% per month per point implies that stocks obtaining the maximum (minimum) score on employee relations of 4 (-4) will outperform (underperform) other stocks in the sample by 3.4% on an annual basis.

However, if we assume that the whole of the employee relations score is no more than the sum of its parts - the employee relations subscores - it can be imagined that some subscores have a significant effect on excess returns, whereas others have no effect at all. To disentangle the effect of the subscores we re-estimate equation (2.5), this time including the subscreens of employee relations as dummy variables. A description of the subscreens and the results are provided in 2.4. The size and significance of the dummies suggests that a few subscreens are responsible for the effect of employee relations on excess returns.

Second, only the concern subscreens have a significant effect on excess returns, but they are not consistent in sign. This implies that simply adding the subscores of strength and concern screens to form overall scores leads to confounding effects. It also suggests that what is a concern from a social perspective is not always a concern from a financial perspective. This is due to the fact that social objectives do not always align with firm financial objectives. For instance, Pension/Benefit Concern (Empcon. D) has a positive influence on future excess returns. A possible explanation is that companies that have substantially underfunded defined benefit pension plan have lower future financial obligations and therefore higher expected future cash flows. However, both objectives can be aligned too. For example, when we look at Poor union relations (Empcon. A) and Workforce reductions

Table 2.2. Carhart regressions, equally weighted KLD portfolios, July 1992 - June 2006

Panel A: KLD Difference Portfolios										
	$\alpha$	t-stat	RM - RF	t-stat	SMB	t-stat	HML	t-stat	MOM	t-stat
Community	3.40%*	1.852	-0.15***	-3.06	-0.04	-0.77	-0.30***	-4.49	0.01	0.46
Diversity	2.36%	0.95	-0.08	-1.47	-0.25***	-4.64	-0.1	-1.66	0.06	0.92
Employee Rel.	0.50%	0.305	-0.07**	-2.08	-0.11***	-3.2	-0.11***	-2.09	0.09**	2.39
Environment	1.13%	0.879	-0.04	-1.52	0.06	1.82	-0.11***	-3.01	-0.03	-1.11
Product	1.48%	0.767	0.02	0.46	0.15**	2.55	-0.25***	-4.01	-0.02	-0.79
Governance	0.92%	0.368	-0.21***	-4.22	0.25***	3.89	0.1	1.29	-0.06	-1.2
J-stat A	9.37		24.96		27.38		23.67		14.44	
	(-0.154)		(0.000)		(0.000)		(0.000)		(-0.025)	
J-stat B	7.32		18.59		19.38		13.22		6.36	
	(-0.293)		(-0.005)		(-0.004)		(-0.040)		(-0.384)	

Panel B: KLD Strength and Concern Portfolios

	$\alpha$	t-stat	RM - RF	t-stat	SMB	t-stat	HML	t-stat	MOM	t-stat
Community Strengths	3.01%	1.45	0.95***	17.66	0.01	0.17	0.49***	4.41	-0.11	-1.77
Community Concerns	-0.38%	-0.13	1.10***	13.4	0.05	0.92	0.79***	5.89	-0.13	-1.48
Diversity Strengths	3.37%	1.34	1.03***	24.25	0.1	1.58	0.39***	3.53	-0.20**	-2.5
Diversity Concerns	0.99%	0.28	1.11***	15.41	0.36***	3.66	0.49***	3.96	-0.26***	-4.87
Employee Strengths	2.68%	1.22	1.07***	24.46	0.20***	3.14	0.43***	4.43	-0.22***	-4.12
Employee Concerns	2.18%	0.73	1.13***	19.79	0.31***	4.03	0.54***	4.05	-0.31***	-3.33
Environment Strengths	0.63%	0.25	0.99***	14.9	0.21***	3.18	0.64***	6.43	-0.19**	-2.56
Environment Concerns	-0.50%	-0.19	1.03***	15.41	0.16***	2.5	0.75***	5.95	-0.16	-1.81
Product Strengths	3.42%	1.19	1.03***	18.27	0.18*	1.86	0.33***	3.05	-0.19**	-3.5
Product Concerns	1.91%	0.95	1.01***	20.34	0.04	0.63	0.58***	4.67	-0.17**	-2.64
Governance Strengths	4.21%	1.14	0.91***	12.13	0.38***	3.11	0.46***	2.69	-0.29***	-3.87
Governance Concerns	3.27%	1.38	1.11***	28.98	0.13**	2.14	0.36***	3.57	-0.23***	-4.39
J-stat A	24.32		32.12		31.84		30.96		29.8	
	-0.018		-0.001		-0.001		-0.002		-0.003	
J-stat B	12.91		NA		22.56		19.67		14.07	
	-0.376				-0.032		-0.074		-0.296	

Notes: In Panel A we estimated for all portfolios in a system GMM framework the regression:  $R(t) - RF(t) = \alpha + \beta[RM(t) - RF(t)] + sSMB(t) + hHML(t) + mMOM(t) + e(t)$ . T-statistics are adjusted following Ferson and Foerster (1994) by a factor  $T/(T-P)$ , where T is the number of time periods and P the number of parameters. We also test the overidentifying restriction generated by the remaining orthogonality conditions when we set one of the parameters to zero for all of the portfolios. For panel A Hansen (1982) shows this test is distributed as  $\chi^2(6)$  under the null since in the restricted case the number of instruments is 36 and the number of parameters is 30 so that the number of over identifying restrictions is 6. In panel B this test is distributed as  $\chi^2(12)$  under the null since in the restricted case the number of instruments is 72 and the number of parameters is 60 so that the number of over identifying restrictions is 12. J-stat A and B denote J-stats from 2-Stage and Iterated GMM, respectively. P-values are reported between brackets. The covariance matrix is computed following Newey and West (1994). The Bartlett spectral density kernel estimator is used to make sure that the covariance matrix is positive semi-definite. For a description of the variables we refer to Table 1. \* 10% significance \*\* 5% significance \*\*\* 1% significance. Not available due to the fact that the iterated estimation procedure did not converge.

Table 2.3. Cross-section regressions of excess stock returns, July 1992 - June 2006

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Community	-0.003	0.011	0.003	0.006	0.058	0.068	0.042
	-0.070	0.231	0.062	0.136	1.26	1.469	0.870
Diversity	-0.049	-0.022	-0.012	-0.009	-0.012	-0.017	-0.046
	-1.018	-0.482	-0.268	-0.202	-0.276	-0.384	-1.104
Employee Rel.	0.045	0.060	0.077*	0.079*	0.071*	0.074*	0.073*
	1.028	1.439	1.897	1.951	1.826	1.908	1.720
Environment	0.020	-0.005	0.034	0.037	0.049	0.038	-0.046
	0.377	-0.09	0.644	0.698	0.942	0.732	-1.105
Product	0.042	0.010	0.062	0.053	0.049	0.045	0.058
	0.615	0.145	0.954	0.850	0.811	0.749	1.146
Governance	0.014	-0.095	-0.093	-0.094	-0.110	-0.104	-0.098
	0.173	-1.183	-1.200	-1.221	-1.479	-1.390	-1.312
Beta	0.163	0.037	0.032	0.019	-0.108	-0.124	-0.327
	0.304	0.070	0.061	0.038	-0.237	-0.271	-0.776
Log(Size)		-0.117	-0.015	-0.019	-0.031	-0.015	-0.041
		-1.913**	-0.240	-0.314	-0.507	-0.251	-0.713

Table 2.3. Cross-section regressions of excess stock returns, July 1992 - June 2006 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(B/M)			-0.477***	-0.482***	-0.591***	-0.608***	-0.637***
			-4.109	-4.19	-5.570	-5.756	-6.481
Returns				0.025	0.014	0.011	0.016
				0.777	0.441	0.351	0.613
Turnover					0.330*	0.291	0.107
					1.803	1.591	0.687
Log(Age)						-0.512***	-0.374**
						-3.779	-2.658
Dummy Russell						-0.002	-0.024
						-0.044	-0.573
Dummy Industry	N	N	N	N	N	N	Y

Notes: This table reports the results on the Fama-MacBeth (1973) regressions. Variables are described in Table 1. Dummy Industry Y (N) indicates whether 39 industry dummies have (have not) been included in the specification. T-statistics are reported below the coefficients. \* 10% significance \*\* 5% significance \*\*\* 1% significance\*\*\*

Table 2.4. Cross-section regressions of excess returns on employee relations screens

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Empstr. A	0.037	0.072	-0.13	-0.154	-0.126	-0.076	-0.025
	0.136	0.258	-0.469	-0.559	-0.458	-0.279	-0.092
Empstr. C	0.088	0.07	0.056	0.077	0.066	0.067	0.083
	0.598	0.468	0.374	0.53	0.489	0.497	0.712
Empstr. D	-0.015	0.015	0.093	0.107	0.15	0.148	0.27
	-0.12	0.123	0.816	0.927	1.349	1.343	2.437**
Empstr. F	-0.083	-0.002	-0.007	-0.007	-0.009	0.018	0.05
	-0.539	-0.016	-0.048	-0.05	-0.066	0.125	0.407
Empstr. X	-0.098	-0.057	-0.032	-0.03	-0.024	-0.03	0.105
	-0.676	-0.397	-0.218	-0.211	-0.169	-0.213	0.74
Empcon. A	-0.544***	-0.485***	-0.394**	-0.355**	-0.325*	-0.322*	-0.158
	-3.102	-2.762***	-2.278**	-2.070**	-1.874	-1.874	-0.982
Empcon. B	-0.119	-0.173	-0.324	-0.314	-0.209	-0.176	-0.038
	-0.553	-0.79	-1.528	-1.478	-1.029	-0.865	-0.199
Empcon. C	-0.425*	-0.494**	-0.506**	-0.492**	-0.464**	-0.412*	-0.402*
	-1.829	-2.155	-2.224	-2.215	-2.144	-1.9	-1.854

Table 2.4. Cross-section regressions of excess returns on employee relations screens (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Empcon. D	0.245	0.254	0.262*	0.282*	0.342**	0.333**	0.355**
	1.539	1.594	1.697	1.824	2.268	2.237	2.321
Empcon. X	-0.005	0.052	-0.288	-0.338	-0.307	-0.383	-0.329
	-0.018	0.199	-1.132	-1.317	-1.204	-1.455	-1.421
Community	0.005	0.017	0.015	0.022	0.071	0.08	0.049
	0.097	0.341	0.307	0.44	1.492	1.666	0.966
Diversity	0.005	0.026	0.044	0.046	0.041	0.035	0.007
	0.096	0.531	0.943	1.021	0.927	0.787	0.179
Environment	-0.032	-0.054	-0.017	-0.011	0.012	0.005	-0.063
	-0.612	-1.022	-0.329	-0.213	0.237	0.095	-1.504
Product	0.055	0.027	0.077	0.067	0.064	0.06	0.067
	0.815	0.395	1.187	1.085	1.057	0.996	1.253
Other	-0.009	-0.126	-0.117	-0.118	-0.128	-0.119	-0.113
	-0.121	-1.597	-1.46	-1.479	-1.664	-1.553	-1.483
Beta	0.068	-0.054	-0.067	-0.079	-0.179	-0.198	-0.349
	0.121	-0.098	-0.122	-0.148	-0.371	-0.41	-0.777

Table 2.4. Cross-section regressions of excess returns on employee relations screens (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Size)		-0.114	-0.005	-0.006	-0.019	-0.005	-0.034
		-1.723*	-0.076	-0.09	-0.289	-0.073	-0.549
Log(B/M)			-0.471***	-0.471***	-0.585***	-0.599***	-0.663***
			-4.114	-4.074	-5.445	-5.591	-6.498
Returns				0.015	0.003	0.001	0.009
				0.474	0.104	0.041	0.324
Turnover					0.252	0.215	0.045
					1.386	1.185	0.292
Log(Age)						-0.484***	-0.356**
						-3.388	-2.486
Dummy Russell						-0.008	-0.03
						-0.164	-0.68
Dummy Industry	N	N	N	N	N	N	Y

Notes: This table reports the results on the Fama-MacBeth regressions. Variables are described in Table 1. Dummy Industry Y (N) indicates whether 39 industry dummies have been (have not been) included in the specification. Empstr. A: strong union relations. Empstr. C: Cash Profit Sharing. Empstr. D: Employee Involvement. Empstr. X: Other Strengths. Empcon A: Poor Union Relations. Empcon. B: Safety Controversies. Empcon C: Workforce Reductions. Empcon D: Pension/Benefits Concern. Empcon. X: Other Concern. T-statistics are reported below the coefficients. \* 10% significance \*\* 5% significance \*\*\* 1% significance

(Empcon. C), we find that both have a negative effect on future excess returns, possibly because they influence future cash flows negatively. Furthermore, the results in column (7) suggest that the effect of poor union relations is industry specific.

The results for Employee relations are in line with other findings in the literature. For instance, Carroll and Niehaus (1998) show that increases in unfunded pension liabilities worsen firms' debt ratings, implying that investors require a premium for firms with underfunded pension liabilities. In addition, pension obligations (Mittelstaedt and Warshawsky, 1993) and liabilities for retiree health benefits (Feldstein and Seligman, 1981) both are negatively related to share prices. Hallock (1998) shows that layoffs are negatively related to cumulative abnormal returns (CARs). Concerning union relations, evidence suggests that union coverage is negatively related to market value (Hirsch, 1991). Finally, to the extent that poor union relations increase the potential for strikes, we note that Kramer and Vasconcellos (1996) and Persons (1995) find that strike announcements result in negative CARs.

### 2.4.3 Book-to-market regressions

In the book-to-market regressions, we measure both the dependent variable as well as the SRI scores at the end of the year. Thus, the regressions indicate whether a stock that has a low book-to-market ratio scores high on one of the SRI dimensions. In Table 2.5 we present the results for two different specifications of the model. In column (1), we report results for the specification including time dummies, clustering standard errors by firm. In column (2), we report results for the specification where we cluster standard errors by both year and firm. The SRI scores are the sum of scores on strength screens minus the sum of scores on concern screens. Based on the predictions from the theoretical literature, we expect that SRI scores are negatively related to book-to-market ratios.

Consistent with theory, we see in Table 2.5 that diversity, environment, and product have a significant negative impact on the book-to-market ratios. Interestingly, governance scores have a significant positive effect on book-to-market. In panel B we estimated the model by treating the strengths and concerns scores separately. Here, we observe that the concern part of the governance score mainly drives the results, suggesting that the market values excessive remuneration of top executives, although causation might run both ways. Another interesting finding in panel B is that both environment strength and concern scores are positively related to book-to-market ratios. This may be due to the fact that the total score can

Table 2.5. Pooled book-to-market regressions

Panel A: Overall KLD scores				
Variable	(1)	T-stat	(2)	T-stat
Community	-0.016	-0.830	-0.007	-0.311
Diversity	-0.047***	-4.440	-0.052***	-4.589
Employee Relations	-0.014	-1.14	-0.013	-0.937
Environment	-0.042***	-3.250	-0.047***	-3.467
Product	-0.046**	-2.21	-0.044**	-2.23
Governance	0.108***	7.08	0.118***	4.187
R&D/Sales	-0.005***	-3.00	-0.005***	-3.595
R&DMissing	0.288***	11.74	0.289***	9.596
Russell3000	-0.001	-0.030	-0.036	-0.915
LogAge	0.098***	7.08	0.093***	7.063
ROE	-0.567***	-7.94	-0.575***	-2.964
Dummy Time	Y		N	
Panel B: Strength and Concern KLD scores				
Variable	(1)	T-stat	(2)	T-stat
Community Strengths	-0.004	-0.2	-0.007	-0.28
Community Concerns	0.054	1.64	0.049	1.28
Diversity Strengths	-0.052***	-3.85	-0.066***	-4.18
Diversity Concerns	0.048	2.46	0.045	1.71
Employee Relations Strengths	-0.013	-0.71	-0.017	-0.78
Employee Relations Concerns	0.023	1.5	0.044	1.35
Environment Strengths	0.080***	3.41	0.090***	3.39
Environment Concerns	0.074***	5.52	0.081***	5.7
Product Strengths	-0.097***	-2.63	-0.085**	-2.25
Product Concerns	0.017	0.69	0.014	0.48
Governance Strengths	0.018	0.65	-0.001	-0.03
Governance Concerns	-0.154***	-8.28	-0.174***	-5.44
R&D/Sales	-0.005***	-3.05	-0.003***	-5.16
R&DMissing	0.299***	12.25	0.287***	8.98
Russell3000	-0.008***	-0.23	0.009	0.25
LogAge	0.085***	6.13	0.063***	4.24
ROE	-0.555***	-7.83	0.003***	2.99
Dummy Time	Y		N	

Notes: This table reports the results of the pooled book-to-market regressions. The variables are described in 2.1. In column (1) we report results for the specification including time dummies, clustering standard errors by firm. Dummy Time Y (N) indicates whether 14 year dummies have (have not) been included in the specification. In column (2) we report results for the specification where we cluster by both year and firm. \* 10% significance \*\* 5% significance \*\*\* 1% significance

be zero when strength and concern screens are of equal size. Finally, it is interesting to note that the overall community and employee relations scores as well as their strength and concern sub scores do not have a significant effect on book-to-market ratios. Stated otherwise, stocks obtaining high scores on community and employee relations do not appear to be overpriced relative to other stocks.

#### **2.4.4 Robustness**

To check the robustness of our results, we performed some additional analyses which are available on request. As a first check, we repeated our portfolio regressions but this time using value-weighted returns instead of equally weighted returns. Results remain qualitatively the same, except that the difference portfolio of employee relations yields a significant positive excess return of 2.81% annually, whereas the excess return on the community difference portfolio becomes insignificant. A second check is splitting the employee relations score into its 10 subscores for the book-to-market regressions. In contrast to the return regressions in 2.4, only some of the strength scores significantly influence book-to-market ratios, while the concern scores do not influence book-to-market ratios. A notable exception to this is Workforce reduction (Empcon C.), which does significantly influence book-to-market ratios.

## **2.5 Conclusions**

In this chapter we set out to investigate the effect of socially responsible investment (SRI) on stock returns. In particular, we want to clarify the existing difference between the theoretical literature suggesting a relation between SRI and stock returns, and most of the empirical literature that does not find a significant relationship. We suggest two potential explanations for this puzzle. First, the aggregate analysis of SRI scores may eliminate a relationship if individual dimensions of SRI have opposite effects on performance. We find little evidence for this explanation. Second, in analyzing stock returns, most researchers control for risk using Fama and French regressions, including the HML factor measuring the sensitivity of a stock to the return difference of stocks with high and low book-to-market ratios. SRI results in lower book-to-market ratios, and as a result, the alphas do not capture SRI effects. We establish that SRI - in particular portfolios that score positive on diversity, environment and product - has a significant impact on stock returns.



## *Chapter 3*

# **International diversification and microfinance**

## **3.1 Introduction**

About ten years ago, microfinance started to become more commercial, and this commercialization is increasing very strongly. Commercial banks in developed and developing economies play an increasing role in funding microfinance institutions. In Pakistan, for instance, a number of private commercial banks have moved into microfinance. In Malaysia, Nepal, and Thailand there are programs stimulating commercial banks to become involved in microfinance. In India the National Bank of Agriculture and Rural Development (NABARD) has recently initiated a program to involve private banks in microfinance. According to recent studies the growth of microfinance in India is led by a number of commercial banks such as ICICI and HSBC together with private venture capital funds and social venture capitalists (Lakshman, 2006; Iyer, 2006).

The commercialization of microfinance has also expanded the traditional services by MFIs. MFIs traditionally focus on microcredit, in the form of small loans to the poor. Currently there is a strong shift from microcredit to microfinance. This broader term reflects the fact that microfinance is not only about providing loans. MFIs also collect savings, provide insurance, and help to distribute and market clients' output (Armendáriz de Aghion and Morduch, 2005). Moreover, new banking technology, such as charge cards, ATMs, the use of cell phones and the internet has begun to enter the microfinance business, helping to reduce costs and improve the

delivery of services.

The funding situation of MFIs also starts to change rapidly. Traditionally, microfinance institutions are mainly funded by private and public donors and aid organizations. Recently, international commercial banks and investors have become increasingly interested in financing MFIs. There is an increase in MFIs for which capital market funding becomes important (see Swanson, undated). The first example of commercial capitalization of MFIs was the creation of an investment fund called Profund, which raised \$23 million to finance Latin American MFIs. In 2006, private investment funds, also known as microfinance investment vehicles (MIVs) held portfolios of MFIs' shares with a total value of \$2.3 billion (CGAP, 2007).

Some microfinance institutions have even gone public, and became commercial banks. The most well-known example is Compartamos in Mexico. Compartamos started in 1990 as a standard MFI by providing joint-liability loans to female borrowers. In 1998 Compartamos became a regulated financial institution, a so-called Sociedad Financiera de Objeto Limitado (SFOL). In 2002 Compartamos, as one of the first MFIs, issued public debt. In April 2007 Compartamos went public and transformed itself into a commercial bank. Driven by increasing access to commercial funding sources, the volume of microfinance loans has risen sharply in recent years, from an estimated USD 4 billion in 2001 to approximately USD 25 billion in 2006 (Deutsche Bank Research, 2007).

Since most MFIs are not deposit-taking institutions and since domestic capital markets are thin, international capital markets will become more and more important for the future funding of MFIs. In the 2004-2006 period, foreign investment in Microfinance already more than doubled, from USD 1.7 billion to around USD 4.4 billion (Deutsche Bank Research, 2007). Approximately 50 percent of the funding of foreign capital to MFIs is channeled through specialized Microfinance Investment Vehicles (MIVs). The number of MIVs has increased rapidly and there are now over 80 in existence MIVs. The main investors in MIVs are individual investors. The share of international financial institutions in MIV funding has declined from 36 percent in 2005 to 30 percent in 2006, while institutional investors are catching up. Since 2004 institutional investors have been expanding their interest in the microfinance industry. There is especially an increasing interest from pension funds to invest in microfinance. An example is the launching of the Institutional Microfinance Fund of the Dutch retail bank SNS, which is almost entirely funded by Dutch pension funds.

To some extent the trend of increasing interest of private and institutional in-

vestors for microfinance can be explained by the increased attention for socially responsible entrepreneurship. However, institutional and private investors are also attracted by the high returns provided by some microfinance institutions. Moreover, as is argued by e.g. Krauss and Walter (2010), microfinance may provide attractive opportunities for portfolio diversification since the risk adjusted returns exhibit low correlations with other assets. This low correlation may be due to the fact that many clients of microfinance institutions are part of the informal economy, which is less sensitive to macroeconomic cycles. This suggests that investing in microfinance could offer diversification benefits to (institutional) investors seeking to reduce their portfolio volatility. In the academic literature, however, we find surprisingly little rigorous testing of this issue.

This chapter investigates whether adding microfinance institutions to a benchmark portfolio of international assets is beneficial for investors by using a mean-variance spanning test. This methodology has been used in several seminal papers studying benefits of international diversification, especially in the context of emerging markets, see e.g. Bekeart and Urias (1996), and De Roon et al. (2001). The spanning methodology has recently also been used to analyze the harmonization of fiscal and economic policy within the European Monetary Union, see Moerman (2008). We are the first using mean-variance spanning tests to examine benefits of investing in MFIs.

The mean-variance spanning methodology allows us to study whether adding microfinance to a benchmark set of risky assets improves the risk-return profile for investors. Since it is not possible to go short in microfinance, we apply a spanning test with short-sale constraints, based on De Roon et al. (2001). We will apply the spanning test to all MFIs for which data are available, for MFIs from different regions, and for different types of MFIs. This analysis helps investors willing to invest in MFIs to determine in which MFIs they should invest.

The few papers that deal with benefits of investing in microfinance only consider correlations between financial indicators of MFIs. In our view, the methodology used in other papers is too restrictive. The advantage of the spanning methodology is that it provides a much better indication of possible diversification benefits of microfinance since this methodology simultaneously considers risk and return.

This chapter is organized as follows. Section 3.2 summarizes the existing literature on possible diversification benefits of investing in microfinance. Section 3.3 and section 3.4 explain the methodology and the data we use, respectively. Section 3.5 presents the regression results. Section 3.6 concludes, and suggests some areas

for further research.

## 3.2 Literature survey

There are only a few papers available which provide some evidence on the possible attractiveness of microfinance for investors. The main examples are: Ahlin and Lin (2006), Gonzalez (2007), and Krauss and Walter (2010). These papers, using different versions of the MixMarket dataset, examine whether microfinance shows low sensitivity to the macroeconomy. Whereas Ahlin and Lin (2006), and Gonzalez (2007) empirically address the question of MFI resilience to domestic macroeconomic shocks, Krauss and Walter (2010) deal with domestic and international shocks.

Ahlin and Lin (2006) use a sample of 112 MFIs from 48 countries for the years 1996-2004. By using within and between panel regressions, they examine whether performance of MFIs is affected by the macroeconomy. They focus on four performance measures: self-sustainability, default rates, costs per borrower, and growth in clientele. Concerning the macroeconomic variables, they use real per capita income growth rates, inflation, labor force participation rates, manufacturing's share in GDP and net foreign direct investment as a fraction of GDP. Their study indicates that the macroeconomic environment is a significant determinant of MFI performance, which questions the relevance of investments in microfinance in order to reduce portfolio risk. However, they also show that MFI success is for a substantial part determined by MFI-specific factors.

Gonzalez (2007) analyzes whether changes in domestic GNI per capita significantly affect MFI portfolio risk, measured by four indicators: Portfolio at Risk over 30 days, Portfolio at Risk over 90 days, Loan loss Rate, and Write-off Ratio. His sample contains 639 MFIs in 88 countries for the period 1999-2006. By using fixed and random effects panel regressions, in which he controls for several variables that may affect portfolio risk, the study shows that only with respect to Portfolio at Risk over 30 days there exists a statistically significant relationship between changes in GNI per capita and portfolio risk of MFIs. Regarding the other three indicators for portfolio risk, he finds no evidence for a relationship between MFI asset quality and changes in GNI per capita, suggesting that microfinance portfolios have high resilience to macroeconomic shocks. His study, therefore, provides some evidence that microfinance may provide attractive opportunities for portfolio diversification.

Krauss and Walter (2010) examine whether microfinance shows low correlation

with international and domestic market performance measures. Their dataset contains annual data for the period 1998-2006. In total they consider 325 MFIs based in 66 emerging market countries. They use fixed-effects panel regressions to examine the relationship of MFI returns, measured by five key financial variables (return on equity, profit margin, change in total assets, change in gross loan portfolio and loan portfolio at risk), to global market risk—measured by the S&P 500, Morgan Stanley Capital International (MSCI) world, and MSCI Emerging Markets indexes—and domestic market risk, measured by domestic GDP. Krauss and Walter (2010) also perform regressions for a sample containing MFIs and emerging market institutions (EMIs), and MFIs and emerging market commercial banks (EMCBs). These regressions aim to show whether MFIs show lower or higher correlations with domestic and global market risk than EMIs or EMCBs. Their analysis shows that MFIs are not correlated with global market movements, whereas MFIs are significantly correlated with the domestic macroeconomy. Relative to EMIs and EMCBs, MFIs seem to be more detached from global capital markets. However, concerning the domestic markets, MFIs and the two benchmarks have comparable correlations. This leads Krauss and Walter (2010) to conclude that “MFIs may have useful diversification value for international portfolio investors away from country risk exposures. For emerging market domestic investors, who may have this ability to a much more limited extent, domestic microfinance investments do not seem to provide significant portfolio diversification advantages” (Krauss and Walter, 2010, p. 106).

Apart from the correlation argument, another straightforward argument in favor of adding microfinance to a portfolio is that microfinance can offer investors a high return for only little risk. However, there are large performance differences between MFIs. Stephens and Tazi (2006), for instance, show that return on assets performance differs substantially between regions. While Latin American and Eastern European and Central Asian MFIs perform quite well, Southern Africa and South Asian MFIs perform worse. In addition, performance seems to differ between types of MFIs, e.g. commercially oriented banks perform better than aid oriented Non-Governmental Organizations (NGOs).

### 3.3 Methodology

In contrast to the papers reviewed in the previous section, we use mean-variance spanning tests to test whether investors can benefit from investing in microfinance.

See De Roon and Nijman (2001) for a survey of mean-variance spanning. The mean-variance framework relies on the assumption that investment decisions of investors are solely made on the basis of the mean-variance properties of assets. Whereas the beta in a CAPM model merely informs us about the correlation between an asset and the market portfolio, a mean-variance spanning test is much more informative. Instead of relying on simple correlations, a spanning test is able to assess whether adding microfinance to a benchmark portfolio allows investors to reach a mean-variance efficient portfolio with a higher mean and a lower variance. By assumption, portfolios that are on the efficient frontier are mean-variance efficient. This means that these portfolios have the highest return for a given variance of all possible portfolios. Put differently, they have the lowest variance for a given level of return of all possible portfolios.

Huberman and Kandell (1987) were the first to suggest a multivariate test of the hypothesis that the minimum-variance frontier of a set of  $K$  benchmark assets is the same as the minimum-variance frontier of the  $K$  assets plus a set of  $N$  test assets. However, the spanning test of Huberman and Kandell (1987) assumes that short sale constraints are absent. Since it is impossible to go short in microfinance, the spanning test of Huberman and Kandell (1987) is not appropriate for our case. Therefore, we use the spanning test with short-sale constraints proposed by De Roon et al. (2001). We assume that short-sale constraints are only imposed on the test asset (microfinance) but not on the benchmark portfolios. We use the same testing procedures as in De Roon et al. (2001). For details, we refer to their article.

Usually the spanning methodology is applied to a portfolio of assets. However, since data on MFIs are only available on a yearly basis for the period 1997 to 2007, we use the return on individual MFIs to perform spanning tests based on a panel. It can be shown that a properly defined average model (a model based on portfolios) follows directly from the panel data model, implying that the coefficients should in theory be the same.<sup>1</sup> In short, we run the following pooled panel regression;

$$R_{2ti} = \alpha + \beta R_{1ti} + \epsilon_{t,i} \quad (3.1)$$

where at time  $t$ , for MFI  $i$ , the test asset returns and benchmark returns are given by the  $K$ - and  $N$ -dimensional vectors  $R_{2t,i}$  and  $R_{1t,i}$ , respectively. In our case, the test

---

<sup>1</sup> The main difference between the two approaches concerns the standard errors. The advantage of the panel approach is that the larger sample allows us to use asymptotic tests. However, for a larger sample, the probability of rejecting any statistical test, and thus also the spanning test, is higher (Granger, 1998).

asset is the return on a set of MFIs. So we restrict ourselves to the case of  $N = 1$ . The test amounts to testing

$$\begin{aligned}\alpha + (\beta\iota_K - 1)\eta_{min} &\leq 0 \\ \alpha + (\beta\iota_K - 1)\eta_{max} &\leq 0\end{aligned}\tag{3.2}$$

where  $\eta$  is the risk-free rate and  $\iota_K$  is a  $K$ -vector of ones. So we test intersection under short sales constraint for a minimum and a maximum value of the risk free rate. The chosen minimum and maximum values of the risk free rate are zero and the expected return on the global minimum variance portfolio of the benchmark assets, respectively.<sup>2</sup> If intersection is rejected, it will also be rejected for all intermediate values of the risk free rate, which implies a rejection of spanning. We can test (3.2) by calculating the test statistic suggested by Kodde and Palm (1986)

$$\xi(\eta) = \min_{\alpha_J \leq 0} (\hat{\alpha}_J - \alpha_J)' \text{Var}[\hat{\alpha}_J(\eta)]^{-1} (\hat{\alpha}_J - \alpha_J)\tag{3.3}$$

where  $\alpha_J$  and  $\hat{\alpha}_J$  are the restricted and unrestricted estimates of Jensen's alpha, respectively. The test statistic is asymptotically  $\chi^2$  distributed with 2 degrees of freedom. Its distribution is given in Kodde and Palm (1986). We determine probabilities using numerical simulation, as proposed by Gouriéroux, Holly, and Montfort (1982).

### 3.4 Data

Our dataset contains annual data on MFIs covering the period 1997 to 2007, and is publicly available data from MixMarket ([www.mixmarket.org](http://www.mixmarket.org)). All numerical data are converted to US dollars at contemporaneous exchange rates. MFIs can voluntarily participate in the MixMarket database, but data entry is closely monitored by MixMarket. Participants have to enclose documentation that supports the data, such as audited financial statements and annual reports. In order to be able to provide such data, reporting MFIs should have an adequate information infrastructure. Therefore, the MixMarket database probably represents a random sample of the best managed MFIs in the world (Kraus and Walter, 2008; Gonzales, 2007).

The data reported by MixMarket is not adjusted for subsidies. As noted by Kraus and Walter (2008), from an investor perspective MFI subsidies can be com-

---

<sup>2</sup> These values are also used by De Roon et al. (2001). Note that they use gross returns, while we use net returns.

pared to a too-big-to-fail (TBFT) support for commercial banks. However, the frequency and size of these subsidies is not certain and thus constitutes an investment risk. Unfortunately, we are not able to account for this risk in the present study. Finally, the number of MFIs has grown explosively over the last eleven years. In 1997 there are only about 25 MFIs in our dataset, while in 2006 there are already 800 MFIs in our portfolio. Therefore, the dataset may suffer from some attrition bias.

Since MFIs are not actively traded and hence have no market returns, we have to rely on return measures based on accounting earnings to estimate an accounting alpha and beta. That is, we use return on equity (ROE) and return on assets (ROA) to proxy for MFI market returns. This approach has the obvious disadvantage that it forces us to compare backward-looking accounting returns with forward looking stock returns (i.e. the benchmark). However, Karels and Sackley (1993) analyze the relationship between market betas and accounting betas in the US banking industry and have found significant correlations. In addition, in the short run, returns from MFI investment are based on past performance, e.g. from interest or dividend payments. Any gain investors obtain from ultimately selling their stake can unfortunately not be incorporated in our tests.

To mimic an (institutional) investor's broad investment portfolio we use global equity and bond indexes. The equity indexes we use to compute returns are the Morgan Stanley Capital International (MSCI) world and emerging markets total return indexes, which have also been used by Kraus and Walter (2008). The bond indexes we use are the JP Morgan Global Broad and JP Morgan Emerging Markets Global Composite indexes. All indexes are in US dollars and obtained from Thomson Datastream.

We will first apply the spanning test to all MFIs for which data are available. Next we will apply the spanning test to MFIs from different regions. That is, we make selections of MFIs from Africa, East Asia and the Pacific, Eastern Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa and South Asia. Finally, we will perform spanning tests for different types of MFIs, i.e. Banks, Credit Unions/Cooperatives, Non-profit (NGOs) and Rural Banks. Summary statistics of all MFIs and the different selections of MFIs are displayed in table 3.1.

Table 3.1. Summary Statistics

Panel A - Microfinance Returns	Number of MFIs	MFI ROE		MFI ROA		Median D/E
		Mean	Std. Dev.	Mean	Std. Dev.	
Regions						
Africa	781	0.048	4.931	-0.031	0.172	1.986
East Asia & the Pacific	377	0.094	0.414	0.008	0.123	2.638
Eastern Europe & Central Asia	645	0.082	0.626	0.040	0.125	1.126
Latin America	918	0.078	0.623	0.018	0.168	2.542
Middle East & North Africa	154	0.086	0.614	0.017	0.088	0.359
South Asia	515	0.242	3.484	-0.019	0.151	5.493
All regions	3390	0.099	2.767	0.004	0.154	2.216
Type of MFI						
Bank	286	0.194	0.718	0.028	0.069	5.345
Cooperative/Credit Union	487	0.311	6.066	0.017	0.085	3.422
Non-bank Financial Institution	957	0.038	0.754	0.013	0.192	1.873
Non-profit (NGO)	1422	0.051	2.227	0.009	0.32	1.385
Rural Bank	151	0.194	0.133	0.033	0.026	5.694

Table 3.1. Summary Statistics, continued

Panel B - Benchmark Returns	Mean	Std. Dev.
MSCI world	0.097	0.182
MSCI emerging markets	0.163	0.330
JPM global	0.063	0.087
JPM emerging markets	0.107	0.101

Notes: In this table we report descriptive statistics on Microfinance returns for regions and types of MFIs. We report the number of MFIs, the mean and standard deviation of yearly MFI return on equity and return on assets. Finally, we report the median debt-to-equity ratio (D/E-ratio). The benchmark stock indexes are (1) MSCI world: the Morgan Stanley Capital International developed markets stocks index and (2) MSCI emerging markets: the Morgan Stanley Capital International developing markets stocks index. The benchmark bond indexes are (1) JPM global; the JP Morgan Global Broad and (2) JPM emerging markets; JP Morgan Emerging Markets Bond Index Global Composite. For these benchmark returns we also report the mean and standard deviation of yearly returns. All returns are denominated in US dollar and the period covered for all returns is 1997-2007.

### 3.5 Results

Table 3.2 gives results of our spanning tests for the different regions and the entire sample of MFIs. Panel A provides the results for MFI return on equity and panel B provides the results for MFI return on assets. Looking at the results on all regions, using all four benchmarks, we see that spanning is rejected at the 1% level for return on equity and at the 10% level for return on assets. For return on assets, spanning is only rejected if we add the JP Morgan Global to the set of benchmarks. Also for return on equity spanning is often more convincingly rejected for bond benchmarks than for stock benchmarks. This suggests that a microfinance investment is particularly valuable as addition to the bond share of a globally diversified portfolio.

Looking at the results per region, we see that spanning is never rejected for Africa. Both in terms of return on assets and return on equity Africa is the worst performer in our sample. From the Microfinance Information Exchange (2006) we can identify three reasons for the relatively poor performance of African MFIs compared to other regions. First, African MFIs have higher operating costs due to the weak infrastructure of African countries combined with the rural markets in which they operate and the high labor costs they face. Second, some African MFIs are subject to interest rate ceilings, which prevents them from earning back their higher operating costs. These are MFIs operating in the WAEMU countries, Namibia, South Africa and Guinea (Microfinance Information Exchange, 2008). Third, in Southern Africa there are several high-inflation economies which face higher financial expenses. Also for Middle-East and North Africa, spanning is almost never rejected. Adding MFIs from Eastern Europe and Central Asia could improve a bond portfolio, in particular the JP Morgan Global bond portfolio. For East Asia and the Pacific spanning is always rejected for return on equity, but never rejected for return on assets. To some extent, we see this discrepancy between the results for return on equity and return on assets also for South Asia. A possible explanation could be that the median debt-to-equity ratio is the highest for East Asia and the Pacific and South Asia. This inflates (deflates) their return on equity (return on assets). Finally, for Latin America spanning is almost always rejected, which makes it the most attractive region to invest in from a diversification perspective.

Table 3.2. Spanning tests by region

Benchmark	Afr.	EA & P	EE & CA	LA	ME & NA	SA	All
Panel A: Return on equity							
MSCI world	0.002 (0.943)	7.478 (0.007)	0.203 (0.614)	9.130 (0.003)	2.620 (0.107)	4.721 (0.035)	6.527 (0.012)
MSCI emerging markets	0.017 (0.872)	8.996 (0.003)	0.000 (0.888)	11.362 (0.001)	1.465 (0.227)	2.235 (0.151)	4.993 (0.030)
MSCI world & emerging markets	0.112 (0.734)	9.367 (0.003)	0.010 (0.862)	11.220 (0.001)	1.214 (0.271)	2.115 (0.149)	4.379 (0.038)
JPM global	0.273 (0.595)	7.196 (0.008)	11.301 (0.001)	8.661 (0.004)	4.332 (0.039)	1.766 (0.188)	5.141 (0.025)
JPM emerging markets	0.460 (0.492)	15.081 0.000	2.225 (0.141)	19.591 0.000	2.374 (0.127)	4.397 (0.045)	7.475 (0.007)
JPM global & emerging markets	0.485 (0.481)	13.642 0.000	1.681 (0.199)	13.073 (0.001)	2.542 (0.114)	4.890 (0.030)	8.309 (0.004)
All stocks & bonds benchmarks	0.504 (0.474)	13.655 0.000	1.804 (0.184)	11.643 (0.001)	2.145 (0.145)	3.320 (0.072)	8.240 (0.005)
Panel B: Return on Assets							
MSCI world	0.000 (0.932)	0.278 (0.571)	7.755 (0.007)	2.403 (0.125)	1.561 (0.214)	0.000 (0.896)	0.133 (0.676)
MSCI emerging markets	0.000 (0.904)	0.261 (0.576)	2.123 (0.153)	3.675 (0.059)	0.002 (0.856)	0.000 0.869	0.088 (0.708)

Table 3.2. Spanning tests by region, continued

MSCI world & emerging markets	0.000 (0.971)	0.289 (0.567)	2.709 (0.103)	3.507 (0.065)	0.000 (0.964)	0.000 (0.931)	0.153 (0.669)
JPM global	0.000 (0.924)	1.348 (0.247)	40.830 0.000	5.568 (0.019)	2.576 (0.112)	0.000 (0.939)	4.489 (0.036)
JPM emerging markets	0.000 (0.819)	1.314 (0.254)	8.117 (0.006)	3.441 (0.069)	0.605 (0.412)	0.000 (0.873)	2.230 (0.144)
JPM global & emerging markets	0.000 (0.839)	1.523 (0.223)	7.791 (0.007)	4.398 (0.040)	0.580 (0.430)	0.000 (0.873)	3.104 (0.086)
All stocks & bonds benchmarks	0.000 (0.872)	1.352 (0.248)	4.829 (0.032)	3.362 (0.072)	0.131 (0.683)	0.000 (0.898)	2.945 (0.093)

Notes: In this table we report the results of our mean-variance spanning tests, where short sales restrictions are imposed on the MFI returns that are added to the benchmark returns. The benchmark stock indexes are (1) MSCI world: the Morgan Stanley Capital International developed markets stocks index and (2) MSCI emerging markets: the Morgan Stanley Capital International developing markets stocks index. The benchmark bond indexes are (1) JPM global: the JP Morgan Global Broad and (2) JPM emerging markets: JP Morgan Emerging Markets Bond Index Global Composite. In panel A, we report the results of our spanning tests when we use MFI return on equity as proxy for MFI returns. In panel B, we report the results of using return on assets. We report Wald statistics and p-values between brackets. Here Afr. Indicates Africa, EA & P indicates East Asia and the Pacific, EE & CA indicates Eastern Europe & Central Asia, LA indicates Latin America, ME & NA indicates Middle East & North Africa and SA indicates South Asia. Finally, All indicates that we test spanning for the entire set of regions.

Table 3.3. Spanning tests by type of MFI

Benchmark	Banks	Cooperative	Non-bank	Non-profit	Rural Bank
Panel A: Return on equity					
MSCI world	13.285 (0.000)	1.029 (0.310)	0.469 (0.487)	3.217 (0.078)	54.858 (0.000)
MSCI emerging markets	4.046 (0.053)	0.771 (0.376)	2.875 (0.096)	1.770 (0.193)	32.232 (0.000)
MSCI world & emerging markets	3.806 (0.053)	0.975 (0.323)	4.525 (0.035)	1.441 (0.231)	40.562 (0.000)
JPM global	14.211 0.000	2.153 (0.143)	1.844 (0.179)	0.832 (0.356)	157.043 (0.000)
JPM emerging markets	5.173 (0.030)	1.552 (0.214)	0.000 (0.934)	7.609 (0.008)	55.002 (0.000)
JPM global & emerging markets	5.804 (0.019)	1.500 (0.221)	0.000 (0.936)	8.864 (0.004)	57.635 (0.000)
All stocks & bonds benchmarks	5.162 (0.026)	1.497 (0.222)	0.017 (0.786)	7.289 (0.008)	56.853 (0.000)
Panel B: Return on Assets					
MSCI world	7.209 (0.008)	2.757 (0.102)	0.952 (0.327)	0.000 (0.911)	69.005 (0.000)
MSCI emerging markets	6.320 (0.013)	1.359 (0.246)	0.193 (0.622)	0.000 (0.894)	54.977 (0.000)

Table 3.3. Spanning tests by type of MFI, continued

MSCI world & emerging markets	6.579 (0.011)	4.368 (0.038)	0.262 (0.593)	0.000 (0.931)	60.442 (0.000)
JPM global	7.245 (0.007)	26.674 (0.000)	5.521 (0.020)	0.000 (0.940)	92.360 (0.000)
JPM emerging markets	6.928 (0.009)	12.193 (0.001)	0.112 (0.683)	0.658 (0.396)	42.229 (0.000)
JPM global & emerging markets	6.091 (0.015)	10.742 (0.001)	0.160 (0.647)	1.331 (0.251)	43.413 (0.000)
All stocks & bonds benchmarks	6.452 (0.012)	16.870 (0.000)	0.061 (0.749)	1.127 (0.287)	43.376 (0.000)

Notes: In this table we report the results of our mean-variance spanning tests, where short sales restrictions are imposed on the MFI returns that are added to the benchmark returns. The benchmark stock indexes are (1) MSCI world: the Morgan Stanley Capital International developed markets stocks index and (2) MSCI emerging markets: the Morgan Stanley Capital International developing markets stocks index. The benchmark bond indexes are (1) JPM global: the JP Morgan Global Broad and (2) JPM emerging markets: JP Morgan Emerging Markets Bond Index Global Composite. In panel A, we report the results of our spanning tests where we use MFI return on equity as proxy for MFI returns. In panel B, we report the results of using return on assets. We report Wald statistics and p-values between brackets.

The results of spanning tests per type of MFI are displayed in table 3.3. We see that spanning is always rejected at the 10% level for banks. This is not surprising, since banks are the most profit-oriented MFIs. Moreover, for rural banks spanning is always rejected at the 1% level. Of all types of MFIs they are the best performers in our dataset, having a high mean return and only a small variance. For Cooperatives / Credit Unions, Non-bank Financial Institutions and NGOs we reject spanning only for some indexes.

### 3.6 Conclusions

This chapter uses mean-variance spanning tests to examine whether it is attractive for investors to add microfinance to their portfolio of risky assets. The analysis suggests that, in general, MFIs can be a valuable addition to a broad portfolio of stocks and bonds. This is a remarkable result, especially if compared to investing in emerging markets, to which investing in microfinance is often compared (see e.g. Kraus and Walter, 2008). De Roon et al. (2001) show that, accounting for short sales restrictions, investors will not benefit from including emerging markets in their portfolio. Our analysis suggests that international investors can benefit from including microfinance in their well-diversified portfolio, even if short-sales restrictions are taken into account. Especially when microfinance is seen as part of the bond share of this portfolio, investing in MFIs seems to be an attractive investment. In fact, many institutional investors invest in microfinance by means of a fixed income investment. Equity finance still constitutes a minor part of microfinance funding.

When we distinguish between different regions, investing in MFIs from Latin America improves the mean-variance frontier almost always, regardless of the benchmark. Conversely, investing in MFIs from Africa never improves the mean-variance frontier. When we distinguish between different types of MFIs, we find that we can reject spanning almost always for banks and rural banks. In particular for rural banks spanning is very convincingly rejected. Conversely, we reject spanning much less for NGOs, Non-bank financial institutions and Cooperatives / Credit Unions. These results have some clear implications for private and institutional investors. In general our analysis suggests that microfinance can provide an attractive investment opportunity EVEN if investors are only interested in risk and return. If it is taken into account that microfinance also has a social aim, and if this is valued by investors, investing in microfinance even becomes more attractive. However, our analysis also indicates that it is more attractive for microfinance investors to invest

in Latin America than in Africa. These investors are also more likely to invest in microfinance banks than in NGOs. Moreover, the analysis suggests that it is especially attractive to add MFIs to the debt part of the portfolio.

The analyses in this chapter have some limitations. We have already pointed at some of these limitations: MFIs are not actively traded and hence have no market returns, so that we have to rely on return measures based on accounting earnings; the data is not adjusted for subsidies, and most importantly, we only have data for 11 years. The latter makes analyses on portfolios unreliable. It is therefore highly important that databases on MFIs' financial variables are developed, which can be used in future research on the attractiveness of microfinance for private and institutional investors. Another possible drawback concerns the limitations of spanning tests. The mean-variance framework relies on the assumption that investment decisions of investors are solely based on the mean-variance properties of assets. In practice, also other characteristics of microfinance may play a role, such as its reputation as a socially responsible investment. Despite these drawbacks we are confident that our analysis provides a valuable first attempt to examine the attractiveness of MFIs for private and institutional investors.



## *Chapter 4*

# **Social investment in microfinance: the trade-off between risk, return and outreach to the poor**

## **4.1 Introduction**

Access to finance is a crucial mechanism for generating persistent economic growth and for reducing world-wide poverty. Although data on access to financial services is still limited, it is clear that there is a huge unmet demand for financial services by the poor. Beck et al. (2007), for instance, estimate that about 40 to 80 percent of the populations in developing economies lack access to the formal banking sector. The access to financial services differs considerably between developing countries. According to the World Bank (2008), less than 50% of the population in most developing countries has a bank account, whereas in most Sub-Saharan African countries more than 80% of the population lacks a bank account.

The limited access to financial services by the poor is due to many reasons, such as a lack of education, a lack of collateral, and the small transactions leading to high costs for financial institutions. Since the late 1970s, however, specialized microfinance institutions serving the poor have tried to overcome these problems in innovative ways e.g. by using group-lending schemes, dynamic incentives and by

hiring local loan officers. The microfinance movement has been impressive, both in terms of new programmes introduced and in terms of the number of clients that are reached. Nowadays, more than 10,000 MFIs in more than 85 countries, serve over 100 million micro entrepreneurs. Driven by increasing access to commercial funding sources, the volume of microfinance loans has risen sharply in recent years, from an estimated USD 4 billion in 2001 to approximately USD 25 billion in 2006. However, according to Dieckman (2007), the microfinance sector still faces a USD 250 billion funding gap, implying that the potential microfinance market is huge.

Currently, nongovernmental organizations serve about half of all microfinance customers, whereas commercial institutions serve less than 20 percent (Cull et al., 2009). As nongovernmental organizations receive about 40 percent of their funding from subsidies, the question arises whether nongovernmental organizations will be able to raise enough subsidies to serve the potential market. Instead, many agree that commercial microfinance, which is the for-profit part of the microfinance sector, is necessary to fund the potential untapped demand for microfinance. Indeed mainstream financial institutions e.g. commercial banks and private and institutional investors are becoming interested in the market for microfinance. Especially pension funds are willing to invest in microfinance. Still, the current proliferation of non-profit organizations and the limited profitability of the very small loans they provide to the poorest borrowers, suggest that subsidies and social investment will continue to be important (Cull et al., 2009).

In this chapter we focus on social investors, which are investors that next to financial performance also value the social performance of their investments. They have started to invest substantially in microfinance: by 2007 they have invested 4 billion dollars in microfinance (CGAP, 2008). Social investors value both the financial and the social returns of microfinance. They are willing to invest in microfinance institutions (MFIs) that are possibly less profitable and more risky, but reach poorer borrowers, i.e. have higher outreach.

One of the most controversial questions about investing in microfinance is whether there exists a trade-off between risk and return on the one hand, and outreach to the poor, on the other. Moreover, if there appears to be such a trade-off, what is the extent to which social investors are willing to accept a decrease in returns and/or an increase in riskiness in order to achieve a higher outreach. In this chapter, we add to the growing evidence that outreach and returns of MFIs are negatively correlated. Moreover, and more importantly, for the first time ever, we try to quantify the trade-off between financial returns of investing in MFIs and outreach

to the poor. More specifically, the chapter aims to derive the price of increasing portfolio outreach, which investors in microfinance have to pay in terms of accepting lower returns or higher risk. The results in this chapter will help social investors to evaluate the trade-offs between financial and social returns.

In terms of the methodology we use, we assume that social investors construct a portfolio of different MFIs and we adapt the mean-variance framework of Markowitz (1958) to construct mean-variance-outreach optimal portfolios. Specifically, we incorporate outreach as an additional constraint in the portfolio optimization procedure to obtain mean-variance efficient portfolios for different degrees of outreach. This chapter proceeds as follows. Section 2 presents our data. Section 3 discusses whether there is a risk-return-outreach trade-off and supports this with some descriptive statistics. Section 4 shows how we quantify the risk-return-outreach trade-off and section 5 concludes.

## 4.2 Data

We use a version of the MixMarket dataset, which covers the period 1997 to 2007, to attempt to quantify the trade-off social investors face between return, risk and outreach. The MixMarket dataset is publicly available from [www.mixmarket.org](http://www.mixmarket.org). All numerical data are converted to US dollars at contemporaneous exchange rates. The number of MFIs has grown explosively over the last eleven years. In 1997 there are only about 25 MFIs in our dataset, while in 2006 there are already 800 MFIs in our portfolio. MFIs can voluntarily participate in the MixMarket database, but data entry is closely monitored by MixMarket. Participants have to enclose documentation that supports the data, such as audited financial statements and annual reports.

In order to be able to provide such data, reporting MFIs should have an adequate information infrastructure. Therefore, the MixMarket database probably represents a random sample of the best managed MFIs in the world (Krauss and Walter, 2009; Gonzalez, 2007). The data reported by MixMarket are not adjusted for subsidies. These subsidies can be seen by investors as shielding a bank from bankruptcy, similar to a too-big-to-fail (TBFT) support for commercial banks (Krauss and Walter, 2008). Nonetheless, the frequency and size of subsidies is not certain and thus constitutes an investment risk. Unfortunately, we are not able to account for this risk in the present study.

### 4.3 The risk-return-outreach trade-off

Before turning to the analysis, we first consider to what extent there is a trade-off between return and outreach and risk and outreach. Considering the trade-off between return and outreach, it is generally agreed that it is more costly to reach poorer borrowers than it is to reach richer borrowers. Obviously, it will be more costly to administer and monitor a 1000 loans of \$200 than doing the same for a single loan of \$200,000. To some extent the increased costs of providing small loans can be covered by economies of scale, although after 2000 clients MFIs tend to have captured most scale benefits (Rosenberg et al., 2009). This is probably due to the labor intensive nature of microfinance in which operating expenses consist mainly of salaries, compared to fixed costs which are relatively low (Rosenberg et al., 2009). The academic literature also finds evidence of a trade-off between performance and outreach. Hermes et al. (2011) find in a stochastic frontier analysis that efficiency decreases with outreach and Cull et al. (2007) find that operating expenses decrease with average loan size

To cover the higher costs of providing small loans, MFIs set higher interest rates (Rosenberg et al., 2009). Due to these higher interest rates, also MFIs that offer relatively small loans are able to make a small profit (Cull et al. 2009). Still, the profit is modest compared to MFIs that offer larger loans. To illustrate, in our dataset the average return on assets for an average loan size below \$1000 is -0.08%, while it is 1.8% for loans above \$1000,-. This difference in performance of small and larger loans, which is statistically significant at 1%, implies that investing in MFIs that offer small loans is probably only of interest to social investors.

Considering the trade-off between risk and outreach, one of the main success stories of microfinance is that also very poor lenders have very high repayment rates. In addition, poor lenders typically operate in the informal sector, which tends to be less correlated to the economy as a whole (Ahlin and Lin, 2006), such that poor borrowers face less macroeconomic risk. This would imply that there is no trade-off, i.e. reaching poorer borrowers is not necessarily more risky. Investors are, however, not so much interested in borrower risk as in MFI risk, which differs among different types of MFIs. Cull et al. (2009) show that the type of organization that typically serves the richer segment of poor borrowers is different from the type of organization that serves the poorer segment. MFIs that serve the richer borrowers typically have a for-profit status, employ an individual lending method, have lower operating costs per loan, are more profitable and rely less on subsidies. By contrast, MFIs that serve the poorest borrowers typically have a non-profit status, employ a

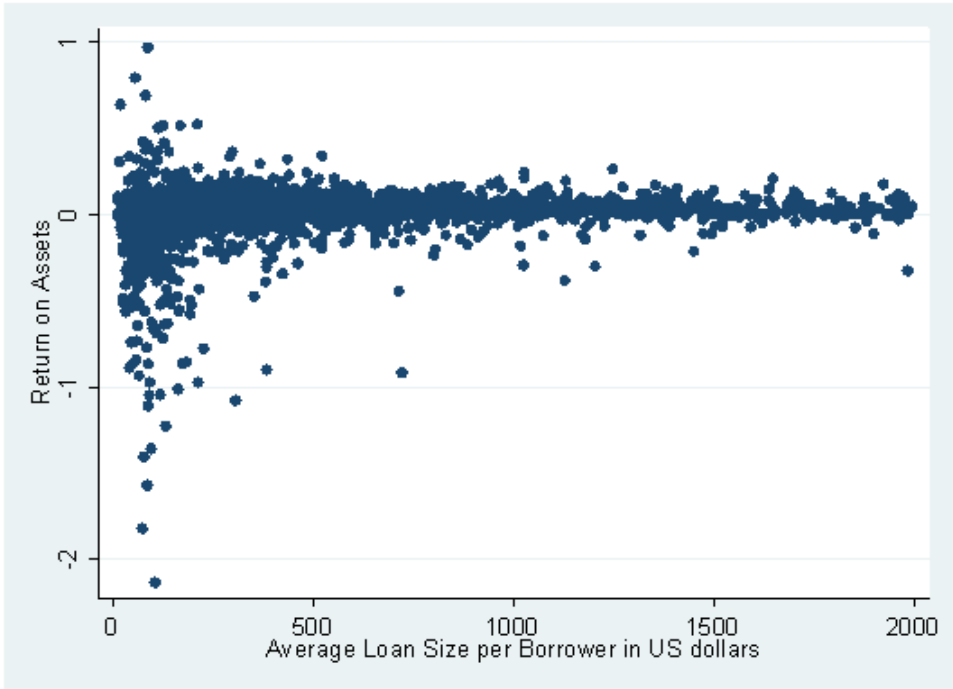


Figure 4.1. Scatter diagram of Return on Assets versus Average loan Size per Borrower

group lending method, have higher operating costs per loan, are less profitable and rely more on subsidies.

There are a number of reasons why the latter types, which are typically non-profit organizations, could be more risky. First, although they do make a profit, their after-subsidy profit depends on the amount of subsidies they receive, which creates a subsidy risk. Second, non-profit organizations are typically smaller than other MFIs: in our dataset their median amount of assets is \$ 1.7 million, whereas the median amount of assets of all other MFIs is \$ 3.7 million. In the advent of financial setbacks, these smaller institutions may have less deep pockets to cushion adverse shocks, like credit contraction or a system-wide decrease in repayment rates. That is, smaller institutions face higher liquidity risk. Third, non-profit organizations usually lack a broad base of deposits, such that they are more exposed to refinancing risk. In most countries MFIs need a bank status to be allowed to take deposits. Indeed, for many nongovernmental organizations that want to expand their business this is an important reason to become a regulated institution.

Figure 4.1 illustrates why MFIs that serve poorer borrowers are more risky. It

shows a scatter plot of MFI return on assets versus average loan size below \$ 2000. Clearly, return on assets is much more dispersed for smaller average loan sizes, especially for average loan sizes below \$500. Consistent with Cull et al. (2009), who show that most customers are served by non-governmental organizations who serve the poorest borrowers, 2579 MFIs have an average loan size below \$1000, whereas 828 MFIs have an average loan size between \$1000 and \$2000. Although we expect that a larger group has higher dispersion, merely due to its size, also an unreported variance test shows that MFIs with an average loan size below \$1000 have significantly higher return on assets variability than those with an average loan size between \$1000 and \$2000.

#### 4.4 Quantifying the risk-return-outreach trade-off

Now we have identified that there is a trade-off between risk, return and outreach, we are ready to quantify this trade-off. In mainstream finance, the trade-off faced by investors in terms of risk and return is usually expressed in the portfolio optimization framework of Markowitz (1958). According to this framework, investors choose optimal portfolio weights to maximize their mean portfolio return and minimize their portfolio standard deviation (from now on expected return and standard deviation, respectively). Optimal portfolios can be depicted as lying on a concave curve, the mean-variance frontier, where each point on the curve is an optimal portfolio. The mean-variance frontier can be drawn in a space with expected return on the y-axis and standard deviation on the x-axis. Portfolios on the mean-variance frontier are optimal in the sense that expected return can only be increased by also increasing risk along the frontier. That is, investors cannot obtain portfolios that lie above the frontier.

To quantify the risk-return-outreach trade-off, we adapt the Markowitz framework to include outreach. In particular, we draw a mean-variance frontier for each value of expected average loan size. We do this by constraining the portfolio optimization problem such that each portfolio on the frontier has a particular expected average loan size, which is the portfolio-weighted average of MFIs' average loan sizes. In this way we create one mean-variance frontier for each level of expected average loan size, where frontiers with a lower expected average loan size lie below those with a higher expected average loan size. By progressively lowering the expected average loan size, we try to find the price of increasing portfolio outreach, which investors pay by accepting lower returns or higher risk. A formal discussion

of this methodology is presented in the Appendix.

For portfolio optimization we need relatively long time spans of data, but on Mixmarket there are only a few MFIs that report returns for a sufficient number of years. Therefore, we choose a sample of MFIs with 9 years of returns, which includes 19 MFIs over the period 1998-2006. To construct the frontiers we use return on equity, although using return on assets yields comparable results. Table 1 reports summary statistics. It shows that the majority of MFIs come from Latin America and the Caribbean and have a non-profit status. In general, non-profits appear to have lower average loan sizes and returns than banks, although there are exceptions and there is considerable heterogeneity in the sample.

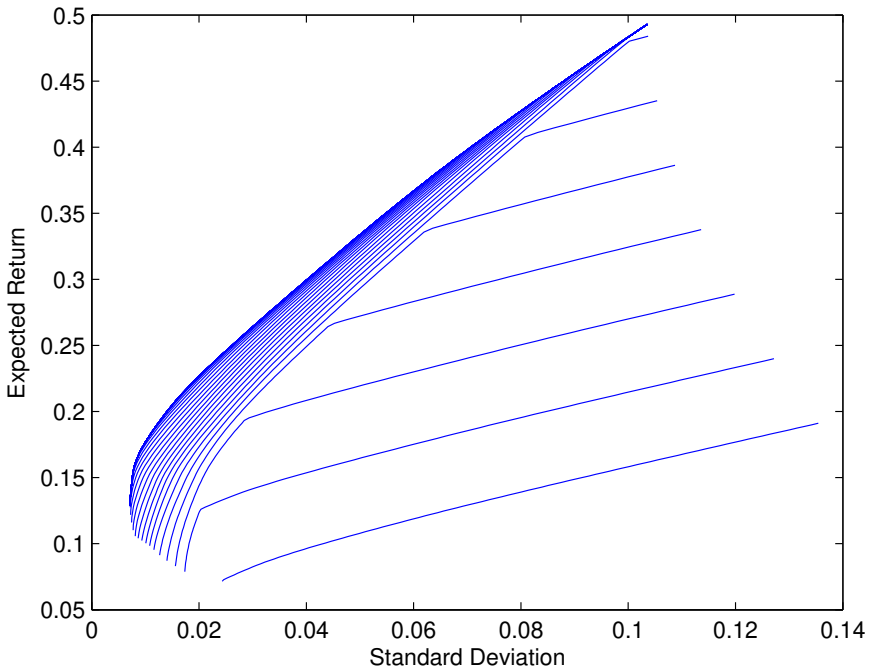


Figure 4.2. Expected return versus standard deviation

Table 4.1. Summary statistics

	MFI	Region	Type	ROA		ROE		ALS	
				mean	std.dev.	mean	std.dev.	mean	std.dev.
1	Asociacin de Consultores para el Desarrollo de la Pequea, Mediana y Microempresa	Latin America and The Caribbean	Non-profit	0.05	0.04	0.19	0.16	347.22	63.71
2	Association Al Amana for the Promotion of Micro-Enterprises Morocco	Middle East and North Africa	Non-profit	0.00	0.15	0.05	0.19	254.67	128.27
3	Association pour la Promotion et l' Appui au Dveloppement de MicroEntreprises	Africa	Non-profit	0.07	0.06	0.14	0.13	693.11	270.47
4	Banco Compartamos, S.A., Institucin de Banca Mltiple	Latin America and The Caribbean	Bank	0.26	0.12	0.49	0.10	264.00	123.35
5	BancoSol	Latin America and The Caribbean	Bank	0.02	0.01	0.14	0.10	1375.78	259.08
6	D-miro	Latin America and The Caribbean	Non-profit	0.05	0.08	0.08	0.11	334.89	183.03
7	FINCA Peru	Latin America and The Caribbean	Non-profit	0.05	0.04	0.06	0.04	143.22	18.27
8	Fondation Zakoura	Middle East and North Africa	Non-profit	0.04	0.05	0.10	0.10	138.89	53.64
9	Fondo Financiero	Latin America	Non-bank Fin.	0.02	0.02	0.11	0.09	1555.22	778.26

Table 4.1. Summary statistics, continued

	Privado PRODEM	and The Caribbean							
10	Fundacin Mundo Mujer Popayn	Latin America and The Caribbean	Non-profit	0.15	0.04	0.24	0.05	366.89	108.99
11	Fundacin WWB Colombia - Cali	Latin America and The Caribbean	Non-profit	0.06	0.04	0.17	0.12	580.22	193.80
12	Fundacin para el Apoyo a la Microempresa	Latin America and The Caribbean	Non-profit	0.08	0.03	0.14	0.05	458.89	72.90
13	Hattha Kaksekar Ltd.	East Asia and the Pacific	Non-bank Fin.	-0.01	0.06	0.01	0.10	275.33	137.68
14	KSK RPK	Eastern Europe and Central Asia	COOP	0.01	0.01	0.02	0.02	5361.44	2504.00
15	MIKROFIN Banja Luka	Eastern Europe and Central Asia	Non-bank Fin.	0.05	0.08	0.12	0.49	1524.89	656.72
16	MiBanco	Latin America and The Caribbean	Bank	0.04	0.02	0.20	0.13	902.11	377.43
17	Programas para la Mujer - Bolivia	Latin America and The Caribbean	Non-profit	0.06	0.02	0.08	0.03	147.22	20.09
18	SHARE Microfin Ltd.	South Asia	Non-bank Fin.	-0.01	0.05	0.06	0.16	83.78	14.47
19	Women's World Banking - Medelln	Latin America and The Caribbean	Non-profit	0.06	0.01	0.16	0.04	444.67	158.92

In this table we report summary statistics for the 19 MFIs in our sample. ROA indicates return on assets, ROE indicates return on equity and ALS indicates average loan size. We selected MFIs that have at least 9 years of returns and for which the covariance matrix is positive definite. The type of MFI can be Non-profit (NGO), Bank, Non-bank financial institution and COOP/Credit union (Cooperative/Credit union).

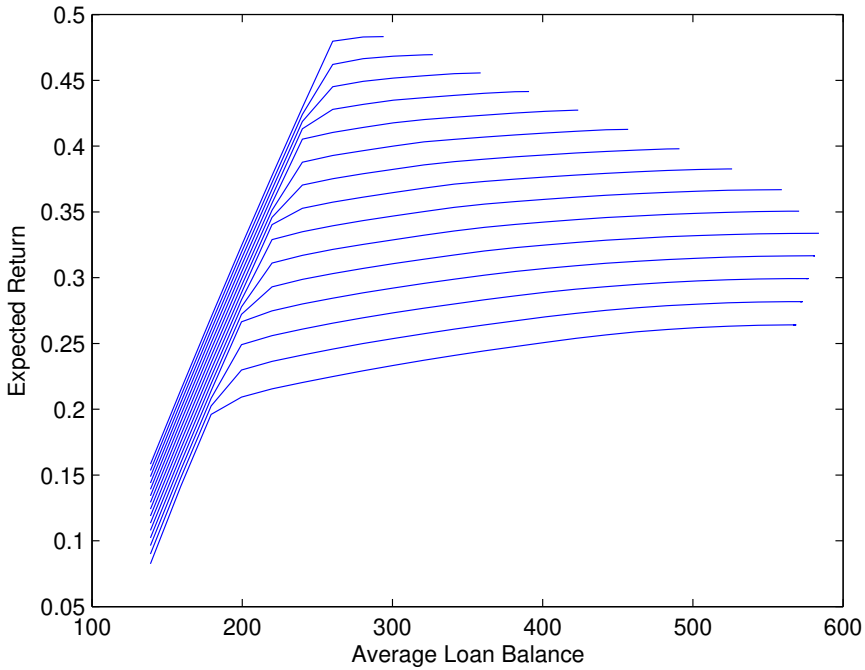


Figure 4.3. Expected return versus average loan balance

For each expected average loan size we construct a mean-variance frontier to obtain Figure 4.2. In Figure 4.2, mean-variance frontiers that have a higher expected average loan size are located above frontiers that have a lower expected average loan size. We see that for high values of expected average loan size the constraint is not very restrictive, but for lower values it becomes rapidly more restrictive. This is apparent from the fast downward shift of the mean-variance frontiers for the lower values of expected average loan size.

To quantify the trade-off between return and outreach, we plot the relationship between expected returns and expected average loan size for different standard deviations, which are vertical cross-sections of Figure 4.2. For instance, to find out how much return decreases for a standard deviation of 6.5% when we decrease expected average loan size, we can draw a vertical line at 6.5% on the x-axis, which intersects all mean-variance frontiers. At each intersection we find a value for expected return and average loans size from which we can construct a plot of expected return versus expected average loan size, i.e. a return-outreach curve. To obtain plots for multiple portfolio standard deviations, we let the standard deviation run

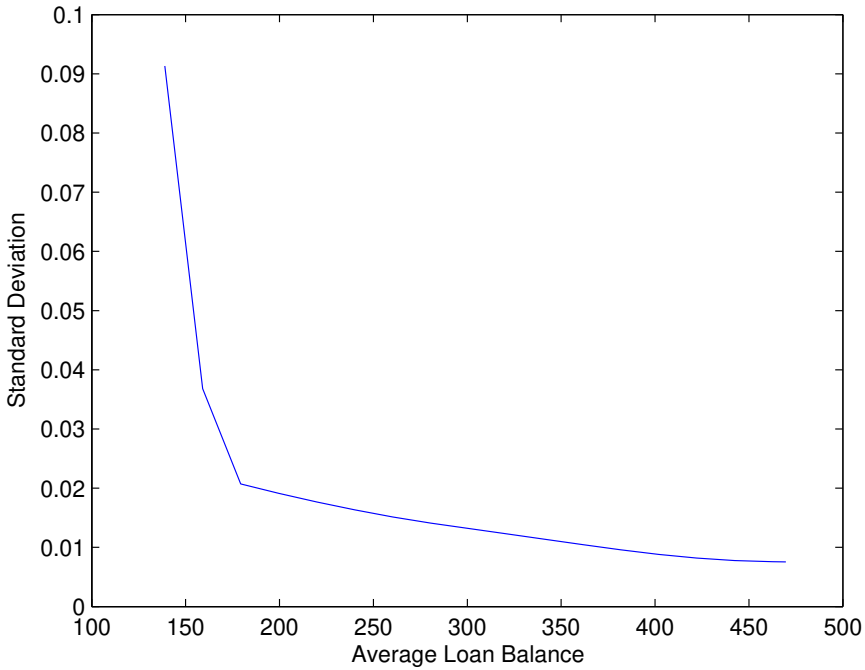


Figure 4.4. Standard deviation versus average loan balance

from 3% to 10% and take 0.5% as step size.

Figure 4.2 shows the resulting return-outreach curves. For a standard deviation of 10% we obtain the highest return-outreach curve and we obtain the lower return-outreach curves as we incrementally lower the standard deviation to 3%. The highest return-outreach curve shows the steepest drop as we lower average portfolio loan size. As we draw curves for lower standard deviations, the drop becomes less steep. So to obtain a lower expected average loan size, expected returns have to fall much more for high standard deviation portfolios than for low standard deviation portfolios. This is due to the fact that the number of assets to choose from with a certain average loan size is much smaller for high standard deviation, high return portfolios.

In Figure 4.3 and Table 4.2 we can also see that for an investor who prefers a standard deviation of 6.5%, which is the seventh curve from below, a decrease in expected average loan size from \$179.36 to \$138.89 costs 11.3% in return on equity. For the same investor, a decrease in portfolio average loan size from \$568.91 to \$179.36, will only cost about 6.8% in ROE. As shown in Table 4.2, in terms of arc

Table 4.2. The Risk-Return-Outreach Trade-Off

Average Loan Size		Expected return		Arc Elasticity (%)		
<b>Panel A: Average Loan Size - Expected Return</b>						
Standard Deviation = 0.03						
\$138.89	→	\$179.36	0.083	→	0.196	320.80
\$179.36	→	\$568.91	0.196	→	0.264	28.30
Standard Deviation = 0.065						
\$138.89	→	\$199.59	0.124	→	0.289	222.20
\$199.59	→	\$526.12	0.289	→	0.383	31.20
Standard Deviation = 0.1						
\$138.89	→	\$240.06	0.158	→	0.430	172.90
\$240.06	→	\$294.24	0.430	→	0.483	58.10
Average Loan Size		Expected return		Arc Elasticity (%)		
<b>Panel B: Average Loan Size - Standard Deviation</b>						
Return = 0.15						
\$138.89	→	\$179.36	0.091	→	0.021	-495.70
\$179.36	→	\$462.62	0.021	→	0.008	-104.90

This table presents the risk-return-outreach trade-off. The arrows are used to indicate the increase in Average Loan Size and the corresponding change in Expected Return or Standard Deviation. The Arc Elasticity indicates the average percentage change in expected return or standard deviation when we decrease Average Loan Size with one percent. This estimator of the actual elasticity, which we cannot measure since we have no functional form, is defined as:  $AE_{x,y} = (x_2 - x_1) / ((x_1 + x_2) / 2) (y_2 - y_1) / ((y_1 + y_2) / 2)$ , where  $x$  indicates either Expected return or standard deviation and  $y$  indicates Average Loan Size. Subscript 1 indicates the value to the left-hand side of the arrow and subscript 2 that to the right-hand side.

elasticity, a percentage decrease in outreach leads to a 320.8% increase in percentage returns in the first case, whereas a percentage increase in outreach only leads to a 28.3% increase in percentage returns in the second case. So a social investor faces a much starker trade-off between returns and average loan size for portfolios that have a lower average loan size.

Next, we quantify the trade-off between risk and outreach by taking a horizontal cross-section of Figure 4.2. That is, for an expected return of 15% we draw a horizontal line at 15% on the  $y$ -axis, which intersects all mean-variance frontiers. At each point where this line intersects a mean-variance frontier, we obtain a different standard deviation and expected average loan size. This yields a plot of the standard deviation against expected average loan size for a return of 15%, which allows us to find out how much the standard deviation increases when we decrease average loan size. We only plot the standard deviation against expected average loan size for one return level, since the range of return values that intersects all

mean-variances curves is very small. Similar to our previous figures, the kink in the graph in Figure 4 shows that there is a very strong trade-off between outreach and risk for low average loan sizes. Specifically, keeping returns constant at 15%, to lower average loan size from \$179.36 to \$138.89 one has to accept an increase in standard deviation of 7%, which corresponds to an arc elasticity of -495.70%.

## 4.5 Conclusion

In this chapter we have shown that social investors in microfinance face a trade-off between, risk, returns and outreach. They face a trade-off between returns and outreach, since it is more costly to borrow to very poor borrowers. They also face a trade-off between risk and outreach, since it is typically more risky to finance the types of MFIs that serve the poorest borrowers. These types of MFIs are typically small non-profit institutions, which are more subject to subsidy, liquidity and refinancing risk than their larger for-profit counterparts. Yet, social investors are willing to accept these trade-offs, i.e. they are willing to give up some returns or to bear more risk to obtain a portfolio of MFIs that on average reduces poverty more.

To quantify how much return investors have to give up, or how much more risk they need to bear to obtain more outreach, this chapter uses the portfolio optimization framework of Markowitz (1958). We find that the trade-offs are not very large for reasonably large average loan size, i.e. average loan sizes above \$180. Yet, for average loan sizes lower than \$180, the trade-off is very pronounced: to lower expected average loan size from \$179.36 to \$ 138.89 an investor has to accept a decrease in return on equity of 11% or alternatively an increase in standard deviation of 7%.

We realize that our results are specific to our small sample and cannot be generalized to the entire population of MFIs. Also, using average loan size as a proxy for outreach is problematic in several ways. A first problem concerns outliers. An MFI can appear to have less outreach, when it has just a few very large borrowers that distort average loan size upward. Second, cross-subsidization of smaller loans with larger loans can increase total outreach. Armendáriz and Szafarz (2009) argue that in richer regions like Latin America, there is actually more scope for cross-subsidization, which implies that the higher average loan size observed in this country are not necessarily a sign of mission drift. Third, comparing average loan size across countries is problematic since different countries are in different stages of development, such that a large loan in one country can be a small loan in

another.

Nevertheless, we believe that the approach presented in this chapter clearly illustrates the trade-offs between financial and social returns of investing in microfinance. While additional research has to be done, and much more data collection is needed before any solid conclusion can be reached, we hope that the techniques presented in this chapter will be valuable for microfinance investors to evaluate the trade-offs between financial and social returns.

## 4.A Methodology appendix

We assess the effect of constraining the mean-variance optimization for different degrees of outreach. We plot the mean-variance frontier by solving the following quadratic program for 100 different expected portfolio returns,  $E[R]$ :

$$\begin{aligned}
 & \min_{\mathbf{x}} \mathbf{x}'\Omega\mathbf{x} \\
 & \text{s.t. } \mathbf{x}'\bar{\mathbf{r}} = E[R]_j \quad j = 1, \dots, 100 \\
 & \quad \mathbf{x}'\boldsymbol{\iota} = 1 \\
 & \quad \mathbf{x} \geq \mathbf{0}
 \end{aligned} \tag{4.A.1}$$

where  $\mathbf{x}$  is a vector of weights,  $\Omega$  is the variance-covariance matrix of returns,  $\bar{\mathbf{r}}$  is vector of expected returns of the assets included in the optimization and  $\boldsymbol{\iota}$  indicates a vector of ones.

We can further constrain this optimization by demanding that the optimal portfolio's average loan balance should be smaller than some pre-specified amount of the expected average loan size,  $E[ALS]$ . The lower  $E[ALS]$  is, the more constrained the optimization is. In this way we can plot a mean-variance frontier for each  $E[ALS]$  by solving the following quadratic program:

$$\begin{aligned}
 & \min_{\mathbf{x}} \mathbf{x}'\Omega\mathbf{x} \\
 & \text{s.t. } \mathbf{x}'\bar{\mathbf{r}} = E[R]_j \quad j = 1, \dots, 100 \\
 & \quad \mathbf{x}'\boldsymbol{\iota} = 1 \\
 & \quad \mathbf{x} \geq \mathbf{0} \\
 & \quad \mathbf{x}'\overline{\mathbf{ALS}} \leq E[ALS] \quad E[ALS] = \min(\overline{\mathbf{ALS2}}), \dots, \max(\overline{\mathbf{ALS2}})
 \end{aligned} \tag{4.A.2}$$

where  $\overline{\mathbf{ALS}}$  is a vector with expected ALS's of the assets and  $\overline{\mathbf{ALS2}}$  is the same vector only with the maximum and minimum value excluded.<sup>1</sup> Obviously, frontiers plotted for higher values of  $E[ALS]$  will lie above frontiers plotted for lower values of  $ALS$ .

---

<sup>1</sup> Note that we do this to prevent portfolio formations based on one asset



## *Chapter 5*

# Do powerful CEOs determine microfinance performance?

## 5.1 Introduction

Literature on microfinance and its effects on poor people in developing countries is voluminous (Hermes and Lensink, 2007), yet still little attention centers on the role of governance in microfinance institutions (MFI). This gap is unfortunate, because good governance can support the viability of MFI operations in terms of both performance and risk management. In some interesting recent contributions to the field of microfinance governance, Mersland and Strøm (2009) find that most governance variables do not affect performance, and Hartarska (2005) reveals that performance-based compensation schemes are not associated with better performance. This study adds to the small body of literature by explicitly focusing on MFI governance and risk taking.

Previous papers have studied the impact of MFI governance on performance, whereas we investigate for the first time the impact of MFI governance on risk. Governance risk is often underestimated (GTZ, 2000), as the current financial crisis illustrates; bank governance did not safeguard banks against their excessive risk taking (OECD, 2009). Executives' incentives to take excessive risks and non-executive directors' limited knowledge of complex financial instruments contributed to the crisis. Therefore, the Basel II agreement explicitly recognizes the critical importance of effective board management and oversight of the risk management process.

Excessive risk taking is an outcome of the board decision-making process, which

means the composition of the board plays a key role. Prior literature indicates that powerful CEOs influence firm risk taking; according to Adams and colleagues (2005), in a firm in which the CEO makes the most relevant decisions, the outcomes are more extreme than they would have been if the firm relied on a consensus among all board members to make decisions. If CEOs are more powerful, their decisions tend to be more extreme, which results in more variable firm performance. In addition, the environment in which the firm operates is important: Adams and colleagues show that CEO power only affects performance variability in industries in which managers have the most decision-making freedom or in high managerial discretion industries (Hambrick and Finkelstein, 1987).

We carefully delineate Adams and colleagues' (2005) theory about group decision-making processes and the extremity of organizational outcomes and thereby offer a theoretical framework to understand the degree of managerial discretion in the microfinance industry, as well as a typology that substantiates how managerial discretion differs across MFI types. We use this typology to posit that managers of nongovernmental organizations (NGOs) have more decision-making freedom than managers of other MFI types. Therefore, CEO power should especially affect NGO performance variability.

However, managerial discretion theory cannot determine whether higher performance variability due to CEO power indicates organizations with great performance, poor performance, or both. Therefore, we also discuss agency and organization theory, which predict negative and positive effects, respectively, of CEO power on performance. In the microfinance context, we argue that the negative effect predicted by agency theory is likely more pronounced than the positive effect predicted by organization theory.

To examine the relationship between performance variability and CEO power, we apply heteroskedasticity tests, a method recently applied by Cheng (2008) and Adams and colleagues (2005), among others. As a robustness test, we use the standard deviations of MFI performance over time as a dependent variable and regress them on CEO power and several controls. Finally, we use quantile regression to test whether CEO power is associated with the worst performing MFIs, as predicted by agency theory, or with the best performing MFIs, as predicted by organization theory. Thus, we reveal what drives the increase in performance variability created by a powerful CEO.

Accordingly, our research offers three contributions. First, it explains why microfinance executives have managerial discretion and delineates how this discre-

tion differs for different organizational types: banks, non-bank financial institutions (NBFIs), credit unions/cooperatives, and non-governmental organizations (NGOs). Second, whereas previous studies have investigated the effect of governance on MFI performance, this study tests the effect of CEO power on MFI performance variability. Third, Adams and colleagues (2005) show that powerful CEOs are associated with both the best and the worst performance; we open the black box to show whether the best or worst performance drives performance variability.

The remainder of this chapter proceeds as follows: In the theoretical section, we explain how group decision making determines the extremity of outcomes. Next we discuss how managerial discretion determines the extent to which managers can influence decision making and how we measure CEO power. We also note alternative theories that could explain extreme performance outcomes. In the hypothesis section, we apply the theory of managerial discretion to microfinance, after which we present our data and provide the findings. We conclude with a discussion of our results and their implications.

## 5.2 Theoretical background

### 5.2.1 Diversification of opinions

To assess the effect of CEO power on the outcomes of the decision-making process, we need to understand how groups make decisions. Both economics and social psychology literature analyze group decision making. The latter considers the specific effect of group processes on different dimensions of group decisions, such as their extremity and riskiness. A natural hypothesis forwarded by Moscovici and Zavalloni (1969, p.125) asserts that the "group consensus" (a group's final choice) is "an averaging, a compromise among individual positions." Experimental research (e.g., Kogan and Wallach, 1966) confirms that group decisions decrease the extremity of post-meeting decisions. In economics literature, Sah and Stiglitz (1986, 1991) compare decision making in different economic systems and claim that group decision making entails a diversification of opinions effect. A group decision is a compromise based on group members' different opinions, such that a project will be undertaken only if a sufficient number of group members agree. Larger groups thus are more likely to reject projects (both good and bad), whereas small groups are less likely to reject them, so the outcomes of the decision-making process are more extreme for small than for large groups. Greater power of a particular group

member has the same effect as decreasing group size: It leads to more extreme outcomes. It follows from Sah and Stiglitz (1986, 1991) that CEO power increases the extremity of the outcomes of group decision making.

Disagreement necessitates compromise, in which case powerful CEOs are better able to get what they want by overcoming the opposition of other executives. According to Pfeffer (1997, p.138), "to demonstrate influence and control, most definitions of power include the idea of overcoming resistance." The ability to overcome resistance should be consistent, to distinguish power from chance (March, 1966). Accordingly, Adams and colleagues (2005, p.1405) define powerful CEOs as "those who can consistently influence key decisions of their firms, in spite of potential opposition from other executives."

Sah and Stiglitz (1986) assume executives disagree because they make judgment errors. To justify this assumption, they argue that information is costly to acquire and people have limited capabilities to gather, absorb, and process information within their limited time available. According to Cannella and colleagues (2009), such limitations especially affect top management teams. Top executives encounter constant complexity and ambiguity; information is often contradictory, complex, and so abundant that it is impossible to analyze it all. Even if executives could interpret and process all available information, they cannot know the strategic situations but must interpret them, because future outcomes depend on many events that are presently unknown. Strategic decision making therefore aligns with what Mischel (1977) calls a weak situation, in which stimuli are many, complex, and ambiguous. In a weak situation, managerial biases, such as experiences, preferences, and personality, influence decision making.

### 5.2.2 Managerial discretion

Every executive makes different decisions when faced with the same situation. Accordingly, to understand firm behavior, we must understand the variation in executives' choices, which has motivated extensive management and organizational behavior literature on managerial discretion (Cannella et al., 2009). The discussion of managerial discretion is part of a long-standing debate regarding whether management can influence organizational destinies. On the one hand, population ecologists argue that inertia prevents executives from adapting quickly enough to changes in their environment, so the environment, instead of managers, determines organizational outcomes (Hannan and Freeman, 1977). On the other hand, strategic choice theorists argue that managers play a fundamental role. Hambrick

and Finkelstein (1987) introduce managerial discretion to bridge these polar views: Executives of some organizations have more discretion than those of other organizations, and their discretion can vary over time. Because managerial discretion varies, strategic choice matters more when discretion is high, whereas environmental selection matters more when discretion is low.

Hambrick and Finkelstein (1987) classify the factors that determine managerial discretion into three main categories: environmental, organizational, and managerial characteristics.

*Environmental characteristics.* Managers' influence over corporate performance differs considerably across industries. Wasserman and colleagues (2001) find that the percentage of variation in the return on assets explained by CEO characteristics varies from 4.6% for paper mills to 41% in hotels, and Hambrick and Finkelstein (1987) assert that some environments simply allow more discretion than others, especially when (1) there is a wide range of options, because then the means-ends linkages are not well understood; and (2) there are no direct constraints. Means-ends linkages are poorly understood in high growth industries, which are characterized by decision making in the entrepreneurial mode and vast numbers of choices in terms of products, target customers, and funding sources. Nor is there any consolidation in the optimal strategies for success, because they remain unknown. In contrast, organizations such as hospitals, public universities, and banks are subject to quasi-legal constraints that limit their discretion. For example, public universities and hospitals depend on governments for much of their budget, and regulated banks are limited in the products they may offer, the reserves they must hold, and their minimum interest rate. Thus, managers are more limited in choosing their customers and determining rates.

*Organizational characteristics.* Several organizational characteristics influence discretion, which we categorize as inertial forces, resource availability, and governance. Inertial forces include size, age, culture, and capital intensity. It is difficult for managers to change large, mature organizations with a very strong culture; they tend to have entrenched modes of operation and often rely on the status quo. Organizations that are capital intensive lack discretion because deviations require large extra investments.

An organization's resources also influence the availability of managerial discretion. Organizations with abundant slack have more options to consider than those with limited resources. Excess cash, unused debt capacity, and extra employees greatly expand the number of available options. In addition, organizational

slack enables CEOs to cope more easily with competing demands from stakeholders (Galbraith, 1973).

Even if the organization as an entity has considerable discretion, internal political conditions determine whether executives ultimately influence its course. Corporate governance arrangements determine the discretion of the CEO compared with other board members and stakeholders. For example, CEOs have more status and therefore discretion when they are also chairpersons of the board or founded the organization. The status of a CEO thus provides a source of formal CEO power.

*Managerial characteristics.* Managerial characteristics such as a CEO's aspiration level and commitment also provide a source of informal CEO power. Those CEOs with more aspiration and commitment tend to engage in broader search behavior and consider more courses of action. In addition, executives with powerful characters can consider controversial options, which less powerful executives would not dare suggest. Referent power, such that the executive is admired and highly respected, also knocks down barriers the executive faces in exercising discretion. It is difficult to measure salient sources of CEO power that are determined by managerial characteristics though, so our measure of CEO power, as we describe in the next section, focuses on structural CEO power.

### 5.2.3 Measures of CEO power

Because CEO power derives from both organizational structure and personal characteristics, it comprises different dimensions, not all of which are easy to measure. In particular, structural power relates to executives' formal positions, the formal organizational structure, and the hierarchical authority of executives within this structure. Therefore, we measure the power CEOs have over other executives on the board, due to their formal positions, titles, or status as a founder.

A measure of structural CEO power is CEO duality, which occurs when a CEO is both the chairperson and the president of the board. This duality gives the CEO the potential to dominate the board of directors and enables the CEO to determine what information other executives receive, control the agenda, and lead board meetings (Daily and Johnson, 1997). Such CEO board domination makes effective executive oversight less likely. Accordingly, management—and the CEO in particular—can more easily make decisions that may be unfavorable to shareholders (Fama and Jensen, 1983) or other stakeholders.

Ownership power represents a dummy variable that indicates whether the CEO is one of the MFI's founders. Founder CEOs tend to have more influence on de-

cision making (Finkelstein, 1992; Nelson, 2003). First, founders have influence *as the focal point* for other decision makers, because of their knowledge, experience, and organizational stature. Second, by *founder imprinting*, they determine the initial organizational form, strategy, and culture. Third, *founder psychological commitment* recognizes that, in addition to income, firms deliver personal psychological benefits. Fourth, founders by definition are the longest tenured members of the organization, and such *founder tenure* results in knowledge and insights that allow the CEO to influence decision making. In addition, CEO board tenure is sometimes included separately as a proxy for CEO power.

#### 5.2.4 Agency and organization theory's effect on performance

The theory that combines diversification of opinions and managerial discretion to argue that powerful CEOs make more extreme decisions does not indicate whether this ability leads to good or bad outcomes (Adams et al., 2005). Nor does it recognize an agency problem; corporate decisions are good or bad because managers disagree. However, it does indicate that firms with powerful CEOs have both the best and the worst performance.

In contrast, agency theory predicts that CEO power hurts financial performance, because the responsibility of the shareholders (principals) gets delegated to agents, who are self-interested and whose goals differ from those of the principal. Because there are many shareholders with only small stakes in the firm, no shareholder can exert direct control, and the CEO gains considerable power over the firm's resources (Jensen and Meckling, 1976). Powerful CEOs thus can pursue their self-interests, to the detriment of firm performance.

According to organization theory though, CEO power may have a positive effect on financial performance. In particular, CEO duality offers the benefits of unity of command, and effective management requires a decision maker to have clear and unambiguous authority over subordinates to avoid confusion about who is in charge (Finkelstein and D'Aveni, 1994; Massie, 1965). Conversely, a lack of duality creates multiple authority relationships that promote conflict among executives (Galbraith, 1977). Strategy formation literature advocates CEO duality, because organizations should have strong executives who set strategic direction. (Finkelstein and D'Aveni, 1994). Finally, CEO duality provides a focal point for company leadership and external accountability, which sends a clear signal to stakeholders that the firm has a clear sense of direction (Finkelstein and D'Aveni, 1994; Salancik and Meindl, 1984).

In response to the juxtaposition of these two perspectives, several authors have developed contingency perspectives, which assert that CEO power is not always good, nor is it always bad. According to Finkelstein and D'Aveni (1994), boards attempt to balance the threat of entrenchment against the benefits of unified command. When performance is low and CEOs have little informal power, CEO duality is beneficial. Conversely, when performance is good and CEOs have much informal power, the risk of entrenchment is too high, which makes CEO duality less desirable. In the latter case, boards may attempt to avoid CEO duality.

Combs and colleagues (2007) also develop a contingency framework, in which the effect of CEO power depends on board composition. It is beneficial to have a high-power CEO when there is an outside director-dominated board that can limit the CEO's self-serving behavior. The firm still benefits from a strategic focus, but without the disadvantages associated with agency problems. Conversely, an inside director-dominated board provides sufficient constraints on CEOs with low power.

Accordingly, CEO power can have a positive effect on performance for some firms but a negative effect for others. This claim has two important implications. First, if the impact of CEO power differs per firm, extreme outcomes across firms can be driven by a combination of agency theory and organization theory arguments, instead of managerial discretion. Second, if either the positive or the negative impact dominates, CEO power has an asymmetric impact. That is, CEO power drives either positive or negative extremes

## 5.3 Hypotheses development

### 5.3.1 Microfinance context

Whether CEO power has an effect on microfinance risk taking relates to the central question whether managers matter for organizational outcomes. Managers only matter when they have a sufficient amount of managerial discretion, as determined by environmental, organizational, and managerial characteristics.

*Environmental characteristics.* In 2008, 1200 MFIs reported to the Microfinance Information eXchange, the leading business information provider for the microfinance industry, and indicated they had 53 million borrowers and 64 million savers and were growing by 25% a year and even more in some countries (CSFI, 2008). To understand the growth of the microfinance sector worldwide, we note an important decision by policy makers in the 1980s and 1990s (Cull et al. 2009): The success of MFIs, with repayment rates greater than 95%, prompted the argument that MFIs

should be profitable as well. If access to finance is more important than its price, the interest rates should be high enough to cover costs. Not all potential microfinance clients can be served profitably, and most clients continue to turn to nonprofit banks (Cull et al., 2009), yet the thrust for financial sustainability has driven growth in the microfinance sector.

As we noted previously, environments that allow more discretion provide a wide range of options for stakeholders and a lack of direct constraints. A high growth industry such as microfinance affords executives considerable discretion, because its means-ends linkages are poorly understood. The goal of MFIs is to serve the millions of people who lack access to banks in a financially sustainable way. However, whether this end should be achieved by commercialization is subject to considerable debate. Commercialization proponents argue that for-profit MFIs could better attract funding and increase lending, and without commercial microfinance, there will not be enough funding to serve everyone. Opponents instead assert that commercialization occurs at the expense of the poorest customers, who cannot be served profitably. Moreover, with its focus on profits, commercialization contributes to overindebtedness and damages the philanthropic image of microfinance. Because this debate has not been resolved, executives should have the discretion to focus on either financial or social objectives.

Furthermore, in the financial sector, prudential regulation centers on (1) the stability of the financial system as a whole and (2) the health of individual deposit-taking institutions (Porteous et al., 2010). Because the microfinance industry is often a very small part of the total financial sector, regulators can afford to ignore MFIs without endangering the stability of the financial system. In addition, in many countries the formal banking industry is regulated by a central bank. Formal financial institutions take liquid deposits from the public and transform them into risky, illiquid loans. If a bank suddenly must return deposits, it may lack the capacity because all funds are tied up in illiquid loans, which prompts the failure of deposit-taking institutions. Central bank regulations attempt to mitigate such risk, but because most MFIs only offer credit products and no savings, they are rarely regulated. Therefore, MFIs have more discretion than their regulated counterparts in the formal banking industry.

Despite these general trends, regulation, growth, and financial sustainability vary greatly across the regions in which MFIs are active. For example, in the regions in our data set (see also Helms, 2006), Latin America has a well-established microfinance sector and the longest tradition of commercially viable microfinance.

Many MFIs are regulated, average loan sizes are relatively large, and competition tends to be fierce, especially in urban areas. In Asia though, microfinance has a more social orientation; China and India have relatively little sustainable microfinance relative to their population, mostly due to extensive historic government involvement in the financial sector. Eastern Europe and Central Asia are relatively new to microfinance. Although they are dominated by NGOs, average loan sizes are high due to the higher income and education levels in this region. Compared with other regions, microfinance institutions have rapidly achieved financial sustainability. Africa fares the worst in terms of financial sustainability. Operating costs are relatively high due to the low population density in rural areas, weak and costly infrastructure, and high labor costs. If microfinance in Africa can overcome these obstacles, it has a large growth potential, because much of the population remains unserved by traditional banks. Finally, microfinance in the Middle East and North Africa is growing very fast, mostly due to two countries, Morocco and Egypt. Still, 70% of MFIs are NGOs that depend on their donors. Although commercial banks are moving down market to offer more microfinance, the concept is largely still perceived as a form of charity and therefore not part of the formal financial system. The growth prospects of any region, combined with its regulatory environments, thus determine the degree of discretion MFIs can obtain from their environment.

*Organizational characteristics.* Because microfinance is relatively young, MFIs also tend to be young organizations without clear rules and procedures or excessive reliance on the status quo. The focus on financial sustainability, combined with the growth and profitability of microfinance, have resulted in considerable organizational slack in the form of cash resources. Moreover, until the recent financial crisis, microfinance was so fashionable that there appeared to be too much funding. According to the Consultative Group to Assist the Poor (C-GAP, 2004), between 2004 and 2006 foreign capital stock in microfinance more than tripled to \$4 billion. The increase offered MFI managers considerable discretion, and by 2008, there were fears that the massive inflow of commercial funding could lead to uncontrolled growth and bad investment decisions.

This abundance fueled the explosive growth of microfinance but also caused a shortage of qualified personnel. The lack of locally trained staff to fill management positions and the poor training of MFI middle management represent significant risk factors (CSFI, 2008), and at the executive level, there are concerns about management quality. Many MFIs still have not invested in management skills, because

their philanthropic culture emphasizes dedication at the expense of professionalism. In particular, MFIs tend to be dominated by visionary CEOs who are very charismatic but lack management skills and strategic flexibility (CSFI, 2008). When middle management is relatively weak, few countervailing forces within the MFI limit the CEO's discretion.

At higher managerial levels, quality is a key problem. One of the weakest features of MFIs is corporate governance (CSFI, 2008), because best practice governance mechanisms from mature markets have had little influence (Hartarska, 2005; Mersland and Strøm, 2009). Despite growth in the microfinance sector, corporate governance has not kept pace. Before the recent financial crisis, good governance seemed unnecessary to attract funding, and the philanthropic status of MFIs reduced demands for accountability (CSFI, 2009).

Corporate governance in microfinance generally focuses on the long-term survival of institutions, along with their social objective to reduce poverty (Labie, 2001). The dual mission-to be financially sustainable while reaching out to the poor-makes corporate governance of MFIs more complicated than that of organizations with only one objective. In addition to investors, stakeholders such as donors, employees, and customers likely have more influence than they would in a regular bank. As we discuss further with regard to the moderating effect of NGO status, this challenge is especially pertinent for nonprofit entities.

*Managerial characteristics.* Many MFIs are dominated by "visionary" CEOs who founded the MFI. It is not uncommon for these founder-CEOs to succeed initially, which invokes admiration from employees and other stakeholders (Labie, 2001). Their reputation then supports their ability to make controversial decisions, such as setting ridiculously high performance goals. Their power base expands further when they appoint friends to key executive places. Among Nelson's (2003) characteristics of founder power, founder imprinting is particularly important for MFIs, because their culture and strategy are determined largely by the social mission. The founder thus determines which customers to serve (e.g., poverty levels) and which lending method to use (e.g., group lending). Founder psychological commitment is similarly important, because MFI founders identify themselves with their social mission. Their aspiration level is likely to offer additional discretion; a founder's psychological commitment may be so high that as the MFI grows, the founder finds it hard to give up a leadership role or has difficulty accepting board oversight (Labie, 2001).

To summarize, MFI offers substantial managerial discretion through high growth,

limited regulation, and a lack of management and governance quality. Also, CEOs make decisions in a weak situation. As the microfinance industry grows and MFIs move forward, CEOs must make strategic decisions that determine the extent to which they reach their financial and social objectives. Because these strategic decisions are not always well understood—by management or by stakeholders—the CEOs have considerable discretion. Combining CEO decision making in a weak situation with the diversity of opinions, we propose that if CEOs have more power to influence decision making, their biases will have a greater effect on outcomes and lead to more extreme decisions, which increase performance variability.

*Hypothesis 1:* CEO power increases MFI performance variability.

### 5.3.2 Moderating effect of organization type on CEO power

The MFI landscape is heterogeneous and includes different organization types, such as banks, state banks, NBFIs, credit unions, and NGOs. Banks are formal, for-profit financial institutions, usually regulated by central banks, that offer savings accounts. Although NBFIs are comparable to banks, they are limited by law in the range of services they can offer; some cannot provide savings accounts. Some MFIs might opt for NBFI status though, which is easier to acquire than bank status (Helms, 2006). Among the nonprofit institutions, credit unions are owned and controlled by their members, who obtain and supply its funding. Finally, NGOs were the pioneers in the microfinance industry and usually are the first to start offering services to the poor in a particular region or to a particular segment of the population. They are supported by donors and thus able to serve the poorest segments of the population.

Managerial discretion differs across organizational types. Table 5.1 shows a typology in which we rank organization types from left to right according to the extent of managerial discretion, such that NGOs have the most discretion and banks the least. This typology also details the organizational characteristics that give NGO executives more managerial discretion.

*Objectives.* Even if they are socially motivated, NBFIs and banks are shareholder firms that have clear financial objectives. In contrast, it is often unclear what NGOs and cooperatives or credit unions aim to maximize; the extent of their focus on the objectives of their workers, clients, and donors is at the discretion of executives (Glaeser, 2003). Controlling an organization with dual objectives is more difficult than controlling one solely dedicated to profits. Reaching the poor also is costly, so an MFI faces a trade-off between achieving its financial versus its social object-

Table 5.1. Managerial Discretion Typology of MFIs

NGOs	Cooperatives / Credit Unions	NBFIs	Banks
Not regulated	Not regulated	Partly regulated	Regulated
Non-distribution constraint	Distribute profits to members	Distribute profits to owners	Distribute profits to owners
Governance not tied to ownership	Governance tied to members	Governance tied to ownership	Governance tied to ownership
Dual objectives	Dual objectives	Financial objectives	Financial objectives
← Most	Managerial discretion		Least →

ives (Hermes et al., 2011). This trade-off implies that MFI managers can justify their bad performance on one criterion by referring to the other; poor financial performance could be attributed to the MFI's social mission, especially because social performance is so difficult to measure. This problem is well known in multitask agency theory but difficult to solve. Holmstrom and Milgrom (1991) show that it is suboptimal to offer variable incentive schemes to the CEO when the firm has dual objectives, one of which is difficult to measure. Even if social performance could be measured easily, variable incentive schemes are often forbidden for NGOs (Hartarska, 2005).

*Profit distribution.* In an important distinction, NGOs are subject to a non-distribution constraint; they cannot distribute profits to any stakeholders. Cooperatives and credit unions distribute excess profits to their members, and NBFIs and banks distribute them to their shareholders. The non-distribution constraint creates NGO commitment not to cheat donors, customers, and workers (e.g., Glaeser and Shleifer, 2001; Hansmann, 1980), as well as considerable organizational slack, because any excess profits are returned to the organization. This situation gives NGO executives considerable managerial discretion, or as Glaeser (2003, p. 2) puts it, "managers of non-profit firms have an almost unmatched degree of autonomy."

*Governance.* The nonprofit nature of NGOs also has important consequences for their governance. First, unlike NBFIs and banks, NGO governance is not tied to ownership. Nonexecutive board members with a financial stake in the MFI have more incentives to practice active oversight, but NGOs' board members usually lack any financial stake in the organization. (GTZ, 2000). These board members generally include donors and clients, who may have limited financial knowledge and experience with risk management.

*Regulation.* External governance mechanisms in the environment in which MFIs

operate can limit discretion, though NGOs are more shielded from these mechanisms than other types of MFIs. In contrast with banks and NBFIs, NGOs and cooperatives/credit unions are not regulated by central banking authorities, which prevents them from offering savings products to clients. Because they do not offer savings products and cannot issue equity, they are more limited than other MFIs in obtaining funding. However, NGOs are better able to obtain donor money; their non-distribution constraint means donations cannot be expropriated. Dependence on donations implies that NGOs are somewhat shielded from another external governance mechanism, namely, competition. Glaeser (2003) shows that nonprofit organizations can be productive in areas in which for-profits, like banks and NBFIs, would lose money and shut down. For example, NGOs typically issue smaller loans than for-profits and thus can cater to the poorest segment of the market that cannot be served by for-profit companies (Cull et al., 2009).

In summary, compared with other MFI types, an NGO offers executives the most managerial discretion. The non-distribution constraints create more organizational slack, and the multiple objectives make it hard for the board to practice active oversight. Furthermore, NGOs typically are not regulated. Therefore, NGO status should positively moderate the effect of CEO power on performance variability.

*Hypothesis 2:* CEO power increases MFI performance variability more strongly in NGOs than in other MFI types.

Next, we consider whether CEO power leads to better performance, as organization theory predicts, or worse performance, as agency theory predicts. According to existing contingency frameworks (Combs et al., 2007; Finkelstein and D'Aveni, 1994), the answer depends on whether there are enough countervailing forces to allow an organization to obtain the benefits of CEO power while avoiding its pitfalls. In this sense, NGOs could benefit from a strong leader, because it is not clear what they aim to maximize (i.e., financial sustainability or social benefits), so executive preferences have a greater influence on organizational outcomes than they would in for-profit MFIs (Glaeser, 2003). To prevent executive conflict, powerful CEOs could set clear objectives that provide the organization with a clear sense of direction (Finkelstein and D'Aveni, 1994).

Yet CEO power has a detrimental effect on performance, as predicted by agency theory, when the CEO is self-interested, which should apply to a lesser extent to nonprofit CEOs whose preferences are at least partly altruistic. Still, Hermes and colleagues (2011) find that social and financial performance are trade-offs, such that

power exercised with an altruistic motive still can harm financial performance. The typology in Table I shows that NGO executives have the most managerial discretion, with few countervailing forces to keep a CEO's self-serving behavior under control. Thus, performance variability should be driven mainly by negative deviations from the mean.

*Hypothesis 3:* NGOs with powerful CEOs suffer the worst, not the best, performance.

## 5.4 Methodology

### 5.4.1 Sample

Our data set is the same as that used by Mersland and Strøm (2009) and consists of information compiled from rating reports.<sup>1</sup> It also contains information from the risk assessment reports of five official microfinance rating agencies—MicroRate, Microfinanza, Planet Rating, Crisil, and M-Cril—approved by the C-GAP (2004) Ratingfund. The C-GAP methodology reveals no major differences in MFI assessments that are relevant to the variables used in this study.<sup>2</sup>

Each rating agency obtains a maximum of four years of MFI financial data and characteristics for its ratings. The reports in our data set cover 280 MFIs from 60 countries gathered during 2000–2007, and most of them refer to the past four years. We annualized and monetized all financial entries. However, the data set does not contain the largest, regulated microfinance banks, which have funders that demand traditional credit ratings, such as those offered by agencies like Standard & Poor's. The virtually unlimited number of very small savings and credit cooperatives also do not appear in the data set, because they generally operate in isolation from the rest of the microfinance industry. We expect the effect of CEO power to be extremely high for these very small MFIs, which often lack adequate governance structures. In this regard, our estimates of CEO power are probably conservative. The 280 MFIs in the data set represent commercial, professionally oriented institutions that have decided to allow themselves to be rated to improve their access to funding, benchmark their status against others, and increase their transparency.<sup>3</sup>

The rating agencies collected the data, which makes our data source more reli-

---

<sup>1</sup> See [www.ratingfund2.org](http://www.ratingfund2.org).

<sup>2</sup> Note that the MixMarket dataset we use in the other chapters does not contain governance information, so we use the Mersland's dataset which does.

<sup>3</sup> See [www.ratingfund2.org](http://www.ratingfund2.org).

Table 5.2. Descriptive Statistics

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max	
<b>Panel A: Summary Statistics</b>							
Return on assets	926	0.01	0.03	0.13	-0.9	0.79	
CEO = chairperson	803	0.12	0.00	0.33	0.00	1.00	
CEO = founder	205	0.34	0.00	0.47	0.00	1.00	
No stakeholder electives	926	0.58	1.00	0.49	0.00	1.00	
Board size	812	7.34	7.00	3.72	2.00	33	
International board members	700	0.56	0.00	1.20	0.00	6.00	
International shareholders	926	0.09	0.00	0.28	0.00	1.00	
CEO = female	768	0.25	0.00	0.44	0.00	1.00	
Individual lending	877	0.57	1.00	0.49	0.00	1.00	
Regulated	925	0.30	0.00	0.46	0.00	1.00	
Urban lending	926	0.36	0.00	0.48	0.00	1.00	
MFI age	923	11.06	8.00	9.24	0.00	80	
Assets (in millions)	919	7.50	3.10	16.00	0.04	250	
ln(Assets)	919	14.94	14.94	1.32	10.61	19.34	
Average loan size	905	772.52	446	1318.12	15	24589	
ln(Average loan size)	905	6.05	6.10	1.09	2.71	10.11	
Branch offices	899	12.54	7.00	19.06	1.00	129	
<hr/>							
Regions	A	EA & P	EE & CA	LA	ME & NA	SA	Total
<b>Panel B: Cross-tabulation number of MFIs per MFI type and region</b>							
Bank	19	5	3	12	0	3	42
NBFI	39	33	33	96	7	5	213
NGO	55	21	95	299	37	32	539
Cooperative/credit union	32	1	7	59	0	5	104
State bank	0	0	0	11	0	0	11
Other	3	0	10	4	0	0	17
Total	148	60	148	481	44	45	926

Notes: ROA = net operating income/average annual assets. CEO = chairperson is a dummy that equals 1 if the CEO and the chair of the board are the same person. CEO = founder is a dummy that equals 1 if the CEO is also the founder of the MFI. No stakeholder electives equals 1 when no clients, donors, or employees serve on the board. Board size indicates the number of MFI board members. International board members indicates the number of international board members. International shareholders equals 1 if an MFI has international shareholders. CEO = female is a dummy that equals 1 if the CEO is a woman. Individual lending equals 1 if the MFI mainly conducts individual lending as opposed to group lending. Regulated equals 1 if the MFI is regulated by banking authorities in the country. Urban equals 1 if an MFI's main market is urban as opposed to rural. MFI age = year - start-up year. Ln(Assets) is the natural logarithm of assets. Ln(Average loan size) is the natural logarithm of (gross outstanding portfolio/number of active credit clients). Branch offices indicates the number of branch offices. The regions are Africa (A), East Asia and the Pacific (EA & P), Eastern Europe and Central Asia (EE & CA), Latin America (LA), Middle East & North Africa (ME & NA) and South Asia (SA).

able than self-reported data sources such as Mixmarket<sup>4</sup> or questionnaires. Compared with those included in the 2006 Mixmarket Annual MFI Benchmarks, the MFIs in our sample are younger and smaller, have fewer credit clients, and hold smaller loan portfolios, though the median loan value is comparable.<sup>5</sup> We present the descriptive panel statistics, together with a description of all variables, in Table 5.2. In Panel A, we note that the average MFI in our sample has about \$7.5 million in assets, an average loan size of \$773, 7 board members, and an age of approximately 11 years. We provide a cross-tabulation of the number of MFIs per region and type in Panel B; we have the most observations for NGOs, followed by NBFIs. In addition, most observations come from Latin America, followed by Eastern Europe and Central Asia and Africa.

## 5.4.2 Methods

To investigate our hypotheses, we use three different methods and consider different aspects of MFI performance variability. Because extreme outcomes can materialize at different points in time for different MFIs, we also address across-MFI performance variability and test our hypotheses using a panel of MFIs in which both across- and within-firm variability should be present. Similar to Adams and colleagues (2005) and Cheng (2008), we apply Glesjer's (1969) heteroskedasticity test to pooled time-series data in two steps. First, we conduct a regression that explains MFI performance according to the following model:

$$ROA_{i,t} = \beta_1 + \beta_2 CEOpower_i + \beta_3 Controls_{i,t} + \epsilon_{i,t} \quad (5.1)$$

where  $ROA_{i,t}$  indicates return on assets for MFI  $i$  at time  $t$ , and  $CEOpower$  is a dummy that indicates either CEO-chairperson duality or CEO is founder. The residuals of this first step correspond to the unexpected part of MFI performance. Therefore, the absolute value of the residuals are a sensible proxy for the unpredictability or variability of MFI performance. Second, to explain the variability of MFI performance, we regress the absolute value of the residuals on the same ex-

---

<sup>4</sup>See [www.mixmarket.org](http://www.mixmarket.org).

<sup>5</sup>Note that we compare medians, because the Mixmarket data contain more very large MFIs. In our data set (MixMarket), the median age is 7 years (9 years), and median total assets are \$2.9 million (\$6.2 million). Furthermore, the MFIs in our data set (MixMarket) have an average of 4,900 (10,000) credit clients and a median average loan size of \$433 (\$456).

planatory variables:<sup>6</sup>

$$|\epsilon_{i,t}| = \gamma_1 + \gamma_2 \overline{CEOpower}_i + \gamma_3 \overline{Controls}_{i,t} + v_{i,t} \quad (5.2)$$

The variability measure  $|\epsilon_{i,t}|$  includes both across-MFI variability and within-MFI variability. Across-MFI variability is not necessarily related to managerial discretion. For example, agency problems could mean CEO power has a negative effect on some MFIs, but organizational theory implies CEO power has a positive effect. These different impacts of CEO power in cross-section could drive performance variability across MFIs. Therefore, to isolate the effect of managerial discretion, we investigate the effect of CEO power on within-MFI performance variability only by regressing the standard deviation of ROA for each MFI over time on the average of our explanatory variables, where the horizontal bars indicate averages over time:

$$std(ROA_{i,t}) = \gamma_1 + \gamma_2 \overline{CEOpower}_i + \gamma_3 \overline{Controls}_{i,t} + v_{i,t} \quad (5.3)$$

Finally, to test Hypothesis 3, we take a closer look at the extremes of the performance distribution. Managerial discretion cannot reveal whether the positive effect of CEO power on performance variability results from positive or negative deviations from the mean. Therefore, we might predict that CEO power has a symmetric impact on performance distribution: a negative impact on the lower quantiles and a comparably positive impact on the upper quantiles. Conversely, Hypothesis 3 considers only a negative impact on the lower quantiles, such that the increase in the standard deviation in Hypothesis 2 reflects negative deviations from the mean.

We use quantile regression to investigate the impact of CEO power on different quantiles of the ROA distribution (Koenker and Hallock, 2001), starting with an ordinary least squares (OLS) approach. For ease of exposition, we ignore the panel structure of the data and label the set of explanatory variables  $X_i$ . With OLS, we estimate parameters  $\beta$  for the conditional mean of ROA,  $E[ROA_i | X_i]$ , which we obtain by minimizing the sum of squared deviations:  $\min_{\beta} \sum_i^n (ROA_i - X_i' \beta)^2$ . Thus, OLS gives parameters for the mean of  $ROA_i$  conditional on  $X_i$ . Instead of obtaining parameters for the conditional mean function, we can obtain parameters for the conditional median,  $Q_{0.5}[ROA_i | X_i]$ , by minimizing the sum of absolute deviations:  $\min_{\beta} \sum_i^n |ROA_i - X_i' \beta|$ . Unlike in OLS, there is no closed form solution for this minimization problem, so we use numerical optimization methods to solve for  $\beta$ . Beyond the conditional median function, it is possible to solve the conditional

---

<sup>6</sup> Note that in both regressions, we use clustered robust standard errors to correct for heteroskedasticity.

quantile function,  $Q_q[ROA_i | X_i]$ , for different quantiles  $q$ . Then the minimization becomes (Cameron and Trivedi, 2005):

$$\min_{\beta} \sum_{i:ROA_i \geq X'_i \beta_q} q |ROA_i - X'_i \beta_q| + \sum_{i:ROA_i < X'_i \beta_q} (1 - q) |ROA_i - X'_i \beta_q| \quad (5.4)$$

This asymmetric weighting procedure ensures that the minimization procedure chooses the conditional quantiles. If  $q = 0.9$ , much more weight is placed on predictions for observations with  $ROA \geq X'\beta$  than for observations with  $ROA < X'\beta$ . Thus, quantile regression enables us to estimate the effect of CEO power for the extremes of the ROA distribution. In the reported regressions, we choose the quantiles  $q = 0.10$  and  $q = 0.90$  and plot the regression coefficients from  $q = 0.10$  to  $q = 0.90$  and their confidence intervals to estimate the effect of CEO power over the entire ROA distribution.

### 5.4.3 Dependent variable

The performance variables typically used to assess the effect of governance variables on performance variability are return on assets, Tobin's Q, and stock returns. The latter two require a firm to be listed on a stock exchange. Most MFIs (except a few commercial organizations like Compartamos in Mexico and Equity Bank of Kenya) are not listed, so we only use return on assets (ROA) as a dependent variable.

### 5.4.4 Independent variables

*Power.* We use two proxies for CEO power. First, CEO = chairperson indicates CEO duality as a dummy variable according to whether the chief executive is also chairperson of the board. As Table 5.2 shows, there is CEO duality only in 12% of the MFIs in our sample, so the distribution of CEO-chairpersons is skewed toward non-duality. Adams and colleagues (2005) note a similar problem in their sample, in which the CEO is a founder in only 9% of the cases. This skew implies that our results are conservative, because the few CEO duality occurrences induce a bias toward no finding. Our second measure of CEO power, CEO = founder, is a dummy variable equal to 1 if the CEO founded the MFI and 0 otherwise. In microfinance, Muhammad Yunus is very powerful, due to his status as the founder of Grameen Bank. The power of CEO-founders is especially interesting to investigate, because with a mean age of 11 years, the MFIs in our sample are relatively young, and

accordingly, 34% of them still have their founders as their CEOs.

*Interaction term.* Hypothesis 2 describes a relationship between two variables (performance variability and CEO power) that depends on a third (NGO status). This relationship can be tested by including an interaction term in the moderated regression (Aiken and West, 1991). We multiply CEO power by NGO status to test the effect of CEO power in NGOs. By definition, the main effect of CEO power thus measures the effect of CEO power in all other types of MFIs. Because we have two proxies for CEO power, we create two interaction effects: CEO = chairman  $\times$  NGO status and CEO = founder  $\times$  NGO status.

### 5.4.5 Control variables

As controls, we include *no stakeholder electives*, a dummy variable that indicates whether there are clients, donors, or employee representatives on the board; *board size*, because larger boards and more stakeholders with different perspectives should increase the effect of diverse opinions; and the number of *international board members* and *international shareholders*, which could offer international knowledge and good governance practices. Furthermore, we consider whether the *CEO is female*, because MFIs serve mainly female customers, who might be better served by a female CEO; Mersland and Strøm (2009) find that a female CEO increases financial performance.

Our *individual lending* variable captures differences in performance that stem from different lending methods. *Regulated* indicates whether the MFI is regulated by banking authorities, which provides a good proxy of lender confidence in the MFI and the costs of implementing regulation. *Urban lending* captures the performance differences between MFIs that operate mainly in urban areas versus in rural areas. With *MFI age*, we measure MFI learning effects. To measure the size of an MFI, we use  $\ln(\text{Assets})$ , which is the natural logarithm of assets and captures MFI scale economies. We proxy for outreach with the natural logarithm of the gross outstanding portfolio divided by the number of active credit clients to capture social performance,  $\ln(\text{AverageLoanSize})$ . This outreach measure helps control for a possible trade-off between social and financial performance. To capture diversification advantages, we use the number of branch offices. We provide a full explanation of these variables in Table 5.2 and we include MFI organizational type and region dummies to control for the MFI type- and region-specific fixed effects.

Table 5.3. Variance F-Tests of Equality of Performance Variance

<b>Panel A. <math>H_0</math>: CEO = chairperson</b>	
CEO = chairperson (std.)	0.09
Number of observations	33
CEO $\neq$ chairperson (std.)	0.07
Number of observations	208
Variance F-test	6.954
P-value	[0.00]
<b>Panel B. <math>H_0</math>: CEO = founder</b>	
CEO = founder (std.)	0.09
Number of observations	69
CEO $\neq$ founder (std.)	0.07
Number of observations	136
Variance F-test	3.618
P-value	[0.03]
<b>Panel C. <math>H_0</math>: MFI = NGO</b>	
MFI = NGO (std.)	0.14
Number of observations	542
MFI $\neq$ NGO (std.)	0.11
Number of observations	389
Variance F-test	13.389
P-value	[0.00]
<b>Panel D. <math>H_0</math>: CEO = chairperson &amp; MFI = NGO</b>	
CEO = chairperson & MFI = NGO (std.)	0.11
Number of observations	21
CEO $\neq$ chairperson or MFI $\neq$ NGO (std.)	0.07
Number of observations	220
Variance F-test	7.447
P-value	[0.00]
<b>Panel E. <math>H_0</math>: CEO = founder &amp; MFI = NGO</b>	
CEO = chairperson & MFI = NGO (std.)	0.12
Number of observations	39
CEO $\neq$ chairperson or MFI $\neq$ NGO (std.)	0.07
Number of observations	166
Variance F-test	4.312
P-value	[0.01]

Notes: We report a robust version of the variance F-test of Brown and Forsythe (1974), in which the mean is replaced by the 10% trimmed mean. We perform an F-test of the difference in the variance of the return on assets and operational costs. For each hypothesis we report standard deviations, the number of observations and a variance F-test.

Table 5.4. Panel Performance Variability as a Function of CEO Power and NGO Status

Dependent variable	Absolute value of ROA residuals							
	<i>Model 1</i>		<i>Model 2</i>		<i>Model 3</i>		<i>Model 4</i>	
Independent variables								
CEO = chairperson	0.029**	-0.014	-0.002	-0.018				
CEO = chairperson × NGO-status			0.044*	-0.025				
CEO = founder					0.007	-0.007	-0.002	-0.011
CEO = founder × NGO-status							0.014	-0.015
No stakeholder electives	-0.016*	-0.009	-0.017*	-0.009	-0.019**	-0.007	-0.023***	-0.008
Board size	-0.003***	-0.001	-0.003***	-0.001	-0.002*	-0.001	-0.002	-0.001
International board members	0.003	-0.003	0.004	-0.003	0.006	-0.004	0.006	-0.004
International Shareholders	0.007	-0.012	-0.003	-0.012	-0.009	-0.012	-0.013	-0.013
CEO = female	0.001	-0.006	-0.001	-0.007	0.003	-0.008	0.003	-0.009
Individual lending	0.000	-0.007	-0.001	-0.007	0.001	-0.007	0.003	-0.007
Regulated	-0.009	-0.006	-0.011*	-0.006	-0.012*	-0.007	-0.019***	-0.007
Urban lending	-0.007	-0.007	-0.007	-0.006	-0.010	-0.007	-0.009	-0.007
MFI age	0.001*	0.000	0.001*	0.000	0.000	0.000	0.000	0.000
ln(Assets)	-0.012***	-0.004	-0.013***	-0.004	-0.014***	-0.004	-0.015***	-0.004
ln(Average loan size)	-0.011**	-0.005	-0.010**	-0.005	-0.001	-0.004	0.000	-0.004

Table 5.4. Panel Performance Variability as a Function of CEO Power and NGO Status (continued)

Dependent variable	Absolute value of ROA residuals							
	<i>Model 1</i>		<i>Model 2</i>		<i>Model 3</i>		<i>Model 4</i>	
Independent variables								
Branch offices	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank	-0.015	-0.033	-0.014	-0.029	-0.004	-0.029	0.000	-0.029
Non-bank financial institution	-0.023	-0.031	-0.025	-0.027	-0.008	-0.026	-0.001	-0.027
NGO	-0.022	-0.029	-0.034	-0.025	-0.019	-0.024	-0.020	-0.025
Cooperative/credit union	-0.044	-0.031	-0.054*	-0.027	-0.054**	-0.027	-0.050*	-0.028
State bank	0.022	-0.032	0.01	-0.029	0.043	-0.026	0.045*	-0.027
Constant	0.351***	-0.071	0.384***	-0.069	0.316***	-0.079	0.316***	-0.079
Observations	481		481		415		415	
Adjusted R-squared	0.166		0.173		0.144		0.152	
AIC	-1339		-1343		-1196		-1208	

Notes: This table reports the estimations of Equation 2. We include MFI type dummies for banks, non-bank financial institutions, cooperatives/credit unions, and state banks, excluding other types. We include region dummies for Africa, East Asia and the Pacific, Eastern Europe and Central Asia, Latin America, and the Middle East and North Africa, excluding South Asia. We report robust standard errors clustered by MFI next to the coefficients. \* Significant at 10%. \*\* Significant at 5%. \*\*\* Significant at 1%.

Table 5.5. Cross-Section Regressions: Performance Variability over Time as a Function of CEO Power and NGO Status

Dependent variable	Standard deviation of ROA							
	<i>Model 1</i>		<i>Model 2</i>		<i>Model 3</i>		<i>Model 4</i>	
Independent variables								
CEO = chairperson	-0.008	-0.02	-0.057**	-0.031				
CEO = chairperson × NGO			0.079**	-0.034				
CEO = founder					0.016	-0.012	-0.008	-0.018
CEO = founder × NGO							0.038**	-0.022
No stakeholder electives	-0.002	-0.012	-0.005	-0.011	0.001	-0.011	-0.002	-0.010
Board size	-0.001	-0.002	-0.002	-0.002	0.000	-0.002	0.000	-0.002
International board members	0.002	-0.005	0.003	-0.005	0.007	-0.005	0.007	-0.005
International Shareholders	-0.012	-0.026	-0.023	-0.025	-0.033	-0.027	-0.035	-0.027
CEO = female	-0.001	-0.011	-0.005	-0.011	-0.006	-0.012	-0.006	-0.012
Individual lending	-0.004	-0.009	-0.001	-0.009	-0.004	-0.008	-0.002	-0.008
Regulated	-0.005	-0.012	-0.006	-0.012	-0.004	-0.015	-0.006	-0.015
Urban lending	-0.002	-0.010	-0.002	-0.010	-0.003	-0.009	-0.004	-0.009
MFI age	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001
ln(Assets)	-0.010**	-0.005	-0.012***	-0.004	-0.016***	-0.004	-0.016***	-0.004
ln(Average loan size)	-0.022**	-0.011	-0.023**	-0.011	-0.011	-0.009	-0.010	-0.009

Table 5.5. Cross-Section Regressions: Performance Variability over Time as a Function of CEO Power and NGO Status (continued)

Dependent variable	Standard deviation of ROA							
	<i>Model 1</i>		<i>Model 2</i>		<i>Model 3</i>		<i>Model 4</i>	
Independent variables								
Branch offices	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank	-0.019	-0.035	-0.035	-0.027	-0.013	-0.040	-0.003	-0.045
Non-bank financial institution	-0.025	-0.036	-0.034	-0.029	0.003	-0.039	0.007	-0.044
NGO	-0.047	-0.032	-0.072 <sup>***</sup>	-0.027	-0.042	-0.029	-0.053	-0.035
Cooperative/credit union	-0.051	-0.034	-0.071 <sup>**</sup>	-0.028	-0.046	-0.032	-0.044	-0.038
State bank	0.012	-0.043	-0.013	-0.041	0.044	-0.037	0.043	-0.041
Constant	0.392 <sup>***</sup>	-0.090	0.459 <sup>***</sup>	-0.092	0.380 <sup>***</sup>	-0.088	0.382 <sup>***</sup>	-0.089
Observations	133		133		112		112	
Adjusted R-squared	0.153		0.188		0.188		0.203	
AIC	-368.6		-373.4		-329.9		-331.2	

Notes: This table reports the estimations of Equation 3. We include MFI type dummies for banks, non-bank financial institutions, cooperatives/credit unions, and state banks, excluding other types. We report robust standard errors next to the coefficient. \* Significant at 10%. \*\* Significant at 5%. \*\*\* Significant at 1%.

Table 5.6. Pooled Quantile Regressions in the NGO Sample

Dependent variable	ROA		ROA		ROA		ROA	
	quantile = 0.10		quantile = 0.90		quantile = 0.10		quantile = 0.90	
Independent variables	<i>Model 1</i>		<i>Model 1</i>		<i>Model 3</i>		<i>Model 3</i>	
CEO = chairperson	-0.121**	-0.050	-0.015	-0.024				
CEO = founder					-0.008	-0.027	0.029	-0.023
No stakeholder electives	0.037	-0.024	-0.018	-0.026	0.050**	-0.022	0.004	-0.022
Board size	0.006*	-0.003	-0.003	-0.002	0.003	-0.003	0.001	-0.002
International board members	-0.017	-0.016	0.007	-0.007	-0.019	-0.017	0.016**	-0.008
CEO = female	0.037*	-0.022	0.065***	-0.017	0.039	-0.028	0.066***	-0.019
Individual lending	0.031	-0.021	-0.006	-0.025	0.006	-0.029	0.008	-0.024
Regulated	0.048	-0.035	-0.026	-0.023	0.063	-0.044	-0.033	-0.038
Urban lending	-0.012	-0.019	-0.01	-0.017	-0.017	-0.026	-0.035*	-0.018
MFI age	-0.002	-0.001	0.001	-0.001	0.001	-0.001	-0.001	-0.001
ln(Assets)	0.018*	-0.01	-0.004	-0.01	0.031**	-0.014	-0.002	-0.014
ln(Average loan size)	0.017	-0.013	-0.008	-0.015	-0.012	-0.013	0.007	-0.016
Branch offices	0.000	-0.001	0.001	0.000	-0.001	-0.001	0.001	-0.001
Constant	-0.467***	-0.157	0.212	-0.161	-0.509***	-0.155	0.088	-0.231

Table 5.6. Pooled Quantile Regressions in the NGO Sample (continued)

Dependent variable	ROA	ROA	ROA	ROA
	quantile = 0.10	quantile = 0.90	quantile = 0.10	quantile = 0.90
Independent variables	<i>Model 1</i>	<i>Model 1</i>	<i>Model 3</i>	<i>Model 3</i>
Observations	315	315	264	264
Pseudo R-squared	0.262	0.175	0.241	0.192

Notes: We report the quantile regression estimations. To correct for possible heteroskedasticity, we use bootstrapped standard errors with 10,000 bootstrap replications. We include region dummies for Africa, East Asia and the Pacific, Eastern Europe and Central Asia, Latin America, and the Middle East and North Africa, excluding South Asia. We report robust standard errors clustered by MFI next to the coefficients. \* Significant at 10%. \*\* Significant at 5%. \*\*\* Significant at 1%.

## 5.5 Analyses and results

To provide initial evidence, in Table 5.3 we present a simple variance F-test of the difference in the ROA variability for our panel. Panels A and B provide support for Hypothesis 1: MFI performance variability is significantly higher for powerful CEOs. Panel C indicates a significant difference in performance variance between NGOs and all other types of MFIs. Panels D and E in turn confirm Hypothesis 2: NGOs with CEO-chairperson duality and NGOs in which the CEO is a founder achieve higher performance variability than NGOs in which there is no CEO-chairperson duality and the CEO is not the founder, respectively. In Panels D and E, the difference in standard deviations is greater than that in Panels A and B, which suggests that CEO power increases performance variability more in NGOs than in other MFIs.

In Table 5.4, we report the results of Glesjer's (1969) heteroskedasticity test. Model 1 shows that the effect of CEO-chairperson duality on ROA variability is positive and significant, in support of Hypothesis 1. With a coefficient of 0.029, it is also economically large. The average absolute value of ROA residuals across all MFI years is 0.06. Moving from an MFI year in which the CEO is not chairperson to one in which the CEO is a chairperson, the absolute value of ROA residuals increases by a factor of 48%. Adams and colleagues (2005) similarly find that having a founder CEO increases the absolute value of ROA residuals by a factor of 18.5%, though they do not find an effect of CEO duality.

In Model 2, we add the interaction between CEO-chairperson duality and a dummy for whether the MFI is an NGO. This interaction effect is positive and significant, in support of Hypothesis 2. Judging from the increase in the adjusted  $R^2$  value, the addition of the interaction effect explains more variance. In addition, the model has a somewhat better fit, judging from the decrease in the Akaike information criterion (AIC). The main effect of CEO-chairperson duality is no longer significant in Model 2. By construction, the main effect in Model 2 measures the effect of CEO-chairperson duality on performance variability for all MFIs other than NGOs; therefore, CEO-chairperson duality has no effect on variability in these other types of MFIs.

Our panel analyses reveal no evidence for Hypotheses 1 and 2 when we use CEO = founder as a power proxy. Model 2 shows that the effect of a CEO-founder on ROA variability is not significant; Model 4 shows that the interaction of CEO = founder and NGO status is not significant either.

Similar to Cheng (2008), we find a negative effect of board size on performance

variability, which matches our expectations based on the diversification of opinions effect. That is, group decisions by bigger boards demand more consensus, resulting in less extreme outcomes. To derive the economic significance of these results, consider an increase in board size of one standard deviation (i.e., 3.72 directors): It decreases the absolute value of ROA residuals by  $-0.003 \times 3.72 = -0.01$ , which implies a decrease in the absolute value of ROA variability of 17%.

Contrary to our expectations, MFIs without stakeholder electives exhibit less performance variability. We expected such a board would be more homogeneous and thus make more extreme decisions. Yet we find a negative effect of being a credit union or cooperative, as we expected, because different cooperative members must agree to reach consensus. In addition, we find that larger MFIs have less performance variability, judging from the negative effect of  $\ln(\text{assets})$  in Models 1-4. Also, MFIs with less outreach (smaller average loan size) are associated with less performance variability in Models 1 and 2, which suggest a possible trade-off between risk and outreach.

We isolate the effect of within-MFI performance variability by estimating Equation 3 without the region dummies, as we show in Table 5.5. The most surprising result is that Models 1 and 3 indicate no effect of CEO power on within-MFI performance variability, but the interaction effects between CEO power and NGO type are significant in Models 2 and 4. In contrast with our panel regression, we find that CEO = founder has a positive effect on performance variability in NGOs, in support of Hypothesis 2, though only at a 10% significance level. The effect is economically sizeable; in NGOs, compared to the average within-MFI standard deviation of 0.05, CEO-chairperson duality and CEO = founder increase this standard deviation by 0.08 and 0.04, respectively. Furthermore, the main effect of a CEO-chairperson becomes significantly negative, which indicates that in MFIs other than NGOs, CEO-chairperson duality decreases performance variability. Finally, the cross-section analyses confirm the panel analyses that larger MFIs and those with lower average loan balances experience less performance variability, which suggests a possible trade-off between risk and outreach.

To investigate Hypothesis 3, we perform quantile regression for a sample of NGOs only. We first consider  $q = 0.10$  and  $q = 0.90$  and display the results of estimating Models 1 and 3 in Table 5.6. The CEO-chairperson duality significantly decreases the ROA by 12% for  $q = 0.10$ , but it has no significant effect for  $q = 0.90$ . Among the worst performing MFIs in our sample, a CEO-chairman duality has a negative effect on performance, but there is no effect for the best performing MFIs.

In support of our panel analyses in Table 5.4, we find no effect of CEO = founder for either the low or the high quantile of the ROA distribution. Finally, the CEO = female variable is positively associated with ROA performance for the high quantile of the ROA distribution, in line with Mersland and Strøm's (2009) finding of a positive effect of CEO = female on average ROA.

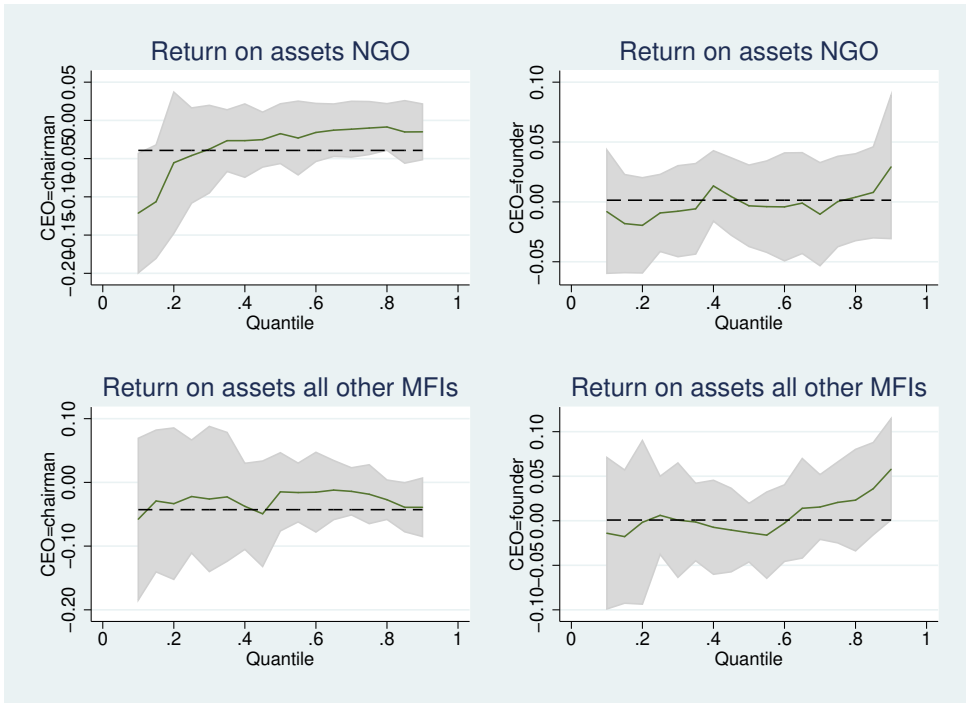


Figure 5.1. Returns on Assets

Instead of two quantile estimates, we can investigate multiple quantiles estimates by plotting them. In Figure 5.1, we therefore include 17 quantile estimates from  $q = 0.10$  to  $q = 0.90$  for CEO-chairperson duality, with a solid line to connect the estimates.<sup>7</sup> The gray area represents the 95% confidence interval, such that a quantile estimate is significant if the grey area does not include the zero line. The OLS estimate is represented by the dotted line. Similar to Mersland and Strøm (2009), we find that the median estimate ( $q = 0.5$ ) of CEO-chairperson duality is insignificant, but it emerges as significant for quantiles below  $q = 0.2$ , because the confidence intervals no longer include 0. Our quantile regressions add a valuable extension to the OLS results regarding the extremes of the performance distribution. We find no

<sup>7</sup> We do not plot quantile estimates below  $q = 0.1$  and above  $q = 0.9$ , because there are insufficient data points in the tails of the distribution to achieve a reasonable degree of accuracy.

effect of CEO = founder on any of the quantiles of the ROA distribution.

To contrast NGOs with other MFIs, we also plot CEO-chairperson duality and CEO = founder for the sample of all other MFIs. The two lower plots in Figure 1 show the results. Neither CEO-chairperson duality nor CEO = founder has any effect on the lower quantiles of the ROA distribution, though CEO = founder has a marginally significant effect on the upper quantiles,<sup>8</sup> which suggests that for other MFIs with high financial performance, which likely have fewer agency problems than NGOs, there are positive effects of CEO power.

## 5.6 Discussion

This chapter offers four key contributions. First, it explains that microfinance executives have substantial managerial discretion and argues how this discretion differs for various organizational types. Second, unlike previous studies that have investigated the effect of governance on MFI performance, we test the effect of CEO power on MFI performance variability. Third, our theory and findings have practical implications for MFI and NGO governance. Fourth, whereas prior research shows that powerful CEOs are associated with both the best and the worst performance, we offer methodological means to clarify whether the best or worst performance drives performance variability.

To our knowledge, this chapter represents the first study to put forth a theoretical framework to understand the degree of managerial discretion in the microfinance industry. Microfinance managers have a substantial degree of discretion, but it differs by organizational type. This finding has important implications for the governance of different types of organizations, because the greater freedom managers have in some types of MFIs enables them to make more extreme decisions. Our study thus complements the theoretical framework of Mersland (2009), which delineates the different costs associated with different ownership types (which we call organizational types), by showing that there are also different risks associated with the different types. In particular, NGO managers have extensive managerial discretion, largely due to their nonprofit nature. Although economic theory acknowledges the greater managerial freedom in nonprofit organizations (e.g., Glaeser, 2003; Glaeser and Shleifer, 2001), it mainly studies the consequences. Our framework applies managerial discretion theory to identify a broad set of factors-

---

<sup>8</sup> An unreported quantile regression, available on request, shows that the positive effect of CEO = founder on  $q = 0.9$  is significant at the 10% level.

environmental, organizational, and managerial-that determine this managerial discretion.

Our study represents still small but growing research into MFI governance. Previous papers have investigated the effect of governance on performance (Hartarska, 2005; Mersland and Strøm, 2009) and governance and efficiency (Hartarska and Mersland, 2009), whereas we focus explicitly on governance and risk taking. A potentially fruitful avenue for further inquiry is the assessment of the moderating role of different stakeholders on CEO power. The diverse set of existing MFI types has diverse stakeholders as well. For example, NGOs often have donor representatives, whereas cooperatives tend to include client representatives on their boards. These representatives provide a diverse set of opinions, such that the diversification of opinions effect could be stronger in MFIs that include stakeholder representatives on their boards. Because of their differing opinions, these stakeholder representatives also might limit CEO power and result in less extreme decisions. As the current financial crisis illustrates, it is relevant from a policy perspective to identify governance mechanisms that lead to excessive risk taking. The case of the Colombian MFI Corposol/Finansol illustrates how bad governance can create a crisis in microfinance (Steege, 1998). Corposol/Finansol was created as an entrepreneurial NGO, dominated by a powerful CEO, and it enjoyed great initial success, based on its NGO culture and inspired CEO leadership. Yet weak control by the board and stakeholders and fast growth, fueled by perverse staff incentives, soon placed the company in serious trouble. Our results confirm that the governance structure has a significant effect on risk, and it is critical for MFIs to adopt a governance structure that effectively manages such risk.

Finally, our study offers a methodological contribution: We use quantile regression to assess whether the increase in performance variability caused by CEO power is due to powerful CEOs' associations with the best or the worst performance. Previous research (Adams et al., 2005; Cheng, 2008) investigates only the effect of governance variables on the variability of performance. Adams and colleagues (2005, p. 1430) cite, from their assessment of the positive effect of CEO power on performance variability, "one potential cost of diluting CEO power: although performance will be less variable, the probability of spectacular performance will also be lower." This statement is correct, as long as the conditional performance distribution is symmetric and CEO power is associated with both the best and the worst performance. If the conditional performance distribution is asymmetric, as in our case, variability increases can reflect either best or worst perform-

ance. Quantile regression then provides additional insights into which effect of governance variables increases risk.

The results of this study should be viewed in light of its limitations though. First, microfinance research is plagued by data limitations. Our data set is the only one available that contains governance variables, but it includes only rated MFIs. It is not representative of the total population of MFIs; in particular, it excludes very big MFIs rated by regular bank rating agencies and very small MFIs that are not rated at all. In addition, because the rating agencies only rated MFIs once during our sample period, our governance variables do not change over time, so we cannot assess the effect of changes in governance over time.

Second, we use CEO-chairman duality and CEO tenure to proxy for the complex notion of CEO power. Although these proxies are relevant for deciding on governance structures, they do not measure the informal power emanating from managerial characteristics such as aspiration level, commitment, and locus of control (Hambrick and Finkelstein, 1987). Nor do our proxies capture other power dimensions, such as expert and prestige power (Finkelstein, 1992).

Third, though our theoretical arguments suggest a causal relationship between CEO power and performance variability, we cannot preclude reverse causality: Higher performance variability could influence CEO power. Demsetz and Lehn (1985) suggest that an increase in uncertainty increases the scope for moral hazard. When uncertainty, as proxied by performance variability, increases, boards should put more constraints on a CEO's behavior. Then performance variability would lead to less CEO power. Alternatively, boards may value CEO power, especially when firm performance is poor (Finkelstein and D'Aveni, 1994), as a signal that there is a "captain in charge of the ship." We find that CEO power is closely associated with the worst NGO performances, which suggests that the worst performances could lead to more CEO power. To resolve this issue, further microfinance research needs instruments for CEO power (e.g., Adams et al., 2005), which are currently not available.

## 5.7 Conclusion

Although literature on microfinance is voluminous, consideration of the governance of MFIs remains scant. This chapter is the first investigation of the effect of governance on MFI risk taking. Building on Adams and colleagues' (2005) work and literature on managerial discretion, we have developed a framework that substanti-

---

ates that MFI managers have managerial discretion, and CEO power increases risk taking. In addition, the degree of discretion differs per organizational type; NGO managers have the most discretion. We find that CEO power is associated with more MFI risk taking, but the increase in risk is especially pronounced for NGOs. Finally, regarding the drivers of the increase in performance variability, we find that CEO power in NGOs is associated with the worst, not the best, performance. Therefore, we conclude that good MFI governance guards against powerful CEOs.

## *Chapter 6*

# Debt enforcement and microfinance risk

## 6.1 Introduction

The impressive growth of microfinance over the last decades has shown that it is possible to offer financial contracts to low-income households. Much of the success of microfinance is due to special innovations like group lending that allow poor borrowers without collateral to finance small business ventures. Loans provided by microfinance institutions (MFIs) enable households at the bottom of the pyramid to finance self-employment activities or to smooth consumption over time, starting with loans as small as \$100.

There are two problems in lending to the poor: lack of information and inadequate collateral. In the last decades microfinance has introduced innovative contracts to solve these problems, the most famous of which is group lending. The theoretical literature that explains the success of group lending schemes is voluminous (e.g. Ghatak and Guinnane, 1999; Gangopadhyay et al. 2005). In addition, a surge of upcoming research uses randomized control trials to determine casual relationships between microfinance and poverty alleviation (see also Banerjee and Duflo, 2010).

Theoretical contributions on contract design in combination with randomized control trials continue to be important tools to determine the ingredients of microfinance's success. Still, no MFI operates in a vacuum: much of the MFI's success depends on the institutional and macroeconomic environment in which it oper-

ates. Except Ahlin et al. (2010), there is little literature that investigates the effect of a country's institutions on microfinance outcomes. This chapter takes the institutional perspective on microfinance: it investigates the effect of a country's credit institutions on MFI risk.

Many countries use courts to enforce debt contracts through bankruptcy or insolvency procedures. Especially in developing countries debt enforcement institutions tend to perform poorly. To illustrate, Djankov et al. (2008) show that in 14 developed countries in their sample, insolvency takes less than a year to resolve, while in nine, mostly poor, countries it takes more than five years. The enormous costs involved in insolvency procedures in developing countries imply that in 80 percent of the cases insolvent businesses end up being sold piece-meal instead of being saved as a going concern (Djankov et al., 2008).

Given the inefficiency of insolvency procedures in developing countries this raises the question whether this affects loan provision to the bottom of the pyramid. Economic theory offers no unequivocal answer. Possibly, loan provision is entirely unaffected by debt enforcement inefficiency. Microfinance clients operate in the informal sector; they lend small amounts and usually have no collateral. Therefore, when microfinance clients default it is not worthwhile to even start insolvency procedures.

Alternatively, microfinance might thrive when debt enforcement institutions are weak, because they act as a substitute for these institutions (Ahlin et al., 2010). Microfinance contracts avoid the need for collateral and thereby possibly also the need for debt enforcement institutions. Therefore, MFIs have a competitive advantage vis-à-vis other financial institutions, which results in a larger and more diverse microfinance market. The resulting diversification advantages serve to decrease MFI risk. Yet, this also implies that MFIs have a competitive disadvantage to formal financial institutions in offering larger loans that do require collateral. Inefficient debt enforcement could thereby reduce the risk-sharing opportunities and increase risks for larger microfinance loans.

Ahlin et al. (2010) find that weak debt enforcement can be both beneficial and detrimental to MFIs, because it is positively related to MFI borrower growth, but negatively related to loan-size growth. Also the creditor rights index and credit information index predict slower loan-size growth. So poor debt enforcement institutions enlarge the microfinance market, but they hamper its growth. The diversification advantages associated with a larger market for microfinance allow MFIs to reduce risk, but slower growth reduces their diversification possibilities and in-

creases risk. Therefore it is an empirical question how credit institutions affect MFI risk.

This question is relevant for several reasons. First, the recent commercialization of microfinance induces a growing number of investment funds to invest in microfinance, usually with a dual goal of financial returns and social impact. Investors evaluate macroeconomic and institutional risks to decide in which countries to invest. When they decide in which MFIs to invest, investors make a trade-off: they weigh return and social impact considerations against risks.

Second, it contributes to the discussion on the fit of microfinance in the broader development process; in particular, does the existence of microfinance aid or hamper the development of credit markets in developing countries? According to Bateman (2010) microfinance does not work: he suggests that currently too much funds flow to microfinance, whose loans are too small to make a contribution to economic growth. The popularity of microfinance crowds out lending to small and medium enterprises (SMEs), which is associated with larger loans that are more likely to be used for the investments in technology and innovation that drive economic growth. Yet, larger loan sizes require collateral, so SME finance suffers from the disadvantages of inefficient credit institutions. If microfinance could substitute for inefficient credit institutions, it could be an attractive alternative for SME finance. Possibly, microfinance could start the development of credit markets when institutions are still weak. As a country's institutions develop, microfinance commercializes and SME funding increases.

There is a large literature on the development of credit markets, dating back to La Porta, et al. (1998,1999) that shows that legal systems and creditor rights are associated with the development of credit markets. This research generally finds that stronger investor protection is related to higher levels of private credit and higher economic growth. Djankov et al. (2007) find that debt enforcement efficiency, creditor rights and information-sharing are positively correlated to the ratio of private credit to gross domestic product (GDP). Other papers examine how credit information sharing increases credit availability (Djankov et al., 2007; Brown et al., 2009), reduces default rates (Japelli and Pagano, 2002) and reduces lending corruption (Barth et al., 2009). Finally, Houston et al. (2010) investigate the links between creditor rights, information sharing and international bank risk taking. They find that stronger creditor rights lead to higher bank risk taking, but also to higher bank growth.

The focus of this chapter is on microfinance risk, but the approach is comparable

to that of Houston et al. (2010). This allows me to indicate whether microfinance complements or substitutes the banking sector<sup>1</sup> in developing countries. In particular, Houston et al. (2010) find that more creditor rights and less information sharing increase bank risk taking. If they would also increase MFI risk, microfinance is complementary, if they would decrease MFI risk microfinance is a substitute for the banking sector.

This chapter contributes to the literature in a number of ways. First, I add to the small body of literature that empirically investigates the effect of institutions and the macro economy on microfinance outcomes. The paper most related to my contribution is Ahlin et al. (2010). Other papers in this literature are Gonzalez (2007) who investigates the link between portfolio-at-risk and economic growth and Kraus and Walter (2008) and Galema et al. (2011) who look at the correlations between MFI performance and international stock market indices. Second, I contribute to the literature on bank risk taking (Laeven and Levine, 2009; Houston and James, 1995), by looking at microfinance risk. Third, I add to the law and development finance literature by showing that credit institutions affect the risk of lending to the poor. Beck et al. (2008) show that financial development especially benefits small firms. Therefore, it is important to understand the effect of legal systems and other institutions on the risk of providing loans to the bottom of the pyramid.

I find strong evidence that inefficient debt enforcement is associated with less MFI risk. That is, the number of days it takes to enforce a debt contract (contract enforcement days) reduces MFI risk. This conclusion is very robust with respect to alternative risk measures, different specifications and estimation techniques. To further explore the assertion that microfinance is a substitute for weak credit institutions, I perform three additional analyses. First, I explore whether debt enforcement inefficiency has a different effect in countries with high and low creditor rights. Countries with high creditor rights—typically common law countries—are more likely to use courts and legal procedures for the proper functioning of their credit market. Therefore, microfinance is more likely to be a substitute for inefficient debt enforcement in these countries, which is confirmed by my finding that debt enforcement inefficiency only decreases microfinance risk in common law countries and countries with high creditor rights.

Second, I investigate the effect of debt enforcement inefficiency on MFI risk for different subsamples in which I distinguish for-profits from nonprofits and regu-

---

<sup>1</sup> In comparison to Houston et al. (2010) this chapter's focus is more on debt enforcement institutions, in addition to creditor rights and information sharing. In unreported results Houston et al. (2010) find no significant effect of debt enforcement inefficiency on bank risk taking.

lated MFIs from unregulated MFIs. Unregulated and non-profit MFIs are the most dissimilar to formal financial institutions, so I expect that only these institutional types are a substitute for formal finance when institutions are weak. This assertion is confirmed: I find that only unregulated and non-profit MFIs take less risk as a result of longer contract enforcement procedures.

Finally, I investigate the effect of the debt enforcement inefficiency on MFI growth. Consistent with Ahlin et al. (2010), I find that contract enforcement days is negatively related to loan-size growth. Inefficient debt enforcement enlarges the market for small loans provided by unregulated and nonprofit MFIs. Yet, it also hamper loan size growth, possibly because larger loans require collateral.

The rest of this chapter proceeds as follows. Section 6.2 delineates the effect of credit market institutions on bank risk and develops hypotheses on how microfinance substitutes for these institutions. Section 6.3 introduces the data and explains how debt enforcement, creditor rights and information sharing are measured. Section 6.4 reports the results that relate MFI risk and portfolio growth to measures of debt enforcement inefficiency, creditor rights and information sharing. Section 6.5 presents robustness checks. Finally, section 6.6 concludes.

## **6.2 Theoretical background**

In this section I first explain the possible effects of inefficient debt enforcement, creditor rights and information sharing on bank risk. Second, I contemplate about their effect on MFI risk. Third, I explain how creditor rights and legal origin could moderate the relation between inefficient debt enforcement and MFI risk. Fourth, I explain how MFI type could moderate the relation between inefficient debt enforcement and MFI risk. Finally, I introduce the possible effect of inefficient debt enforcement, creditor rights and information sharing on portfolio growth.

### **6.2.1 Bank risk: the effect of debt enforcement, creditor rights and information sharing**

Debt enforcement efficiency is determined by the way in which law regulates the operation of courts. In a theoretical model of an ideal court, a debt dispute between an MFI and a borrower can simply be solved by a third party on fairness grounds, without the use of lawyers, courts and written procedures on how arguments and evidence are presented. Unfortunately, in reality dispute resolution is highly form-

alized, with formal procedures that describe the steps of the insolvency process. In many countries these highly formalized procedures lead to huge delays. Considering one of my main variables, contract enforcement days, Djankov et al. (2003) estimate that check collection takes 60 days in New Zealand, while it takes 527 days in Colombia and 645 days in Italy. Djankov et al. (2008) show that rich countries are much more efficient at debt enforcement than the poorer ones. They manage much more often than poorer countries to keep the company as a going concern, at lower transaction cost and in a shorter time span.

The story that emerges from Djankov et al. (2008) is that developing countries follow the rich ones and introduce elaborate bankruptcy procedures to save and rehabilitate insolvent firms. In rich countries these procedures typically succeed in preserving the firm as a going concern, despite their excessive costs in terms of time and money. By contrast, in developing countries these procedures almost always fail in saving the firm; 80 percent of insolvent businesses end up being sold piece-meal. So per capita income is a crucial determinant of the quality of the debt enforcement process. There are exceptions though: rich countries like United Arab Emirates and Italy have very inefficient debt enforcement, while lower-middle income countries like Bosnia, Jamaica and Colombia do rather well. This implies that GDP per capita alone is unlikely explain all the variation of debt enforcement inefficiency.

Inefficient debt enforcement increases risk; when it becomes more costly and time-consuming to enforce a debt contract, bank lending becomes more risky, all else equal. Inefficient debt enforcement makes it more difficult to enforce repayment and in the event of default banks are less likely to recover the full amount of the loan, which makes them less willing to provide loans. The direct effect of creditor rights on bank risk-taking is similar to that of the quality of debt enforcement. Weak creditor rights lead to lower recovery rates in the event of default, which increases risk. Moreover, borrowers are inclined to take more risk when creditors are not well protected. So weak creditor rights make bank lending more risky.

Yet, inefficient debt enforcement and lack of creditor rights could also induce banks to take less risk. They may, for instance, extend loans to a smaller set of (possibly saver) borrowers or increase interest rates to compensate for lower recovery rates. Consistently, Djankov et al. (2007, 2008), show that inefficient debt enforcement is associated with less private credit provision, while stronger creditor rights are associated with more private credit provision.

## 6.2.2 MFIs: the effect of debt enforcement, creditor rights and information sharing

It is far from clear that the determinants of risk in the formal banking sector can be extrapolated to MFIs, because they are very different. First, many MFIs are still subsidized, which means they are to some extent shielded from risks that endanger their existence: as long as they are able to raise enough subsidies, they can continue to exist even if they are financially unsustainable.

Second, MFIs serve clients that operate in the informal sector, who lack collateral and obtain relatively small loans that are subject to high transaction costs. Therefore lenders to the poor face several problems (Ghatak & Guinnane, 1999). First, there is only limited information on poor borrowers, so it is difficult to ascertain what kind of a risk the potential borrower is (adverse selection). Second, once the loan is made the lender has to make sure she utilizes the loan properly, so she will be able to repay it (moral hazard). Third, the lender has to learn how her project really did in case she is not able to repay (auditing costs). Fourth, the lender has to find methods to force repayment if the borrower is reluctant to do so (enforcement).

The first three problems are asymmetric information problems that are too costly to solve for the MFI or for which the proper information sharing institutions are absent. Nonetheless, microfinance information sharing institutions are potentially beneficial. Janvry et al. (2010) show that the introduction of a microfinance credit bureau results in a dramatic improvement in the repayment performance of new individual clients and an increase of the loan sizes of group borrowers. In addition, large numbers of poorly repaying individuals and group clients are ejected as a result of the introduction of the credit bureau. In Bolivia, the law initially forbade private credit bureaus, while its public credit registry refrained from collecting information on the microfinance sector. This resulted in massive overborrowing and a large repayment crisis in the microfinance sector in the late 1990s. Therefore, the Bolivian government now allows private credit agencies, some of which specifically focus on microfinance. Other countries in the world are also witnessing the start-up of microfinance information sharing, especially in regions where there is much competition (Luoto et al., 2007).

Still, microfinance credit information is often not available because in many countries microfinance credit registries are still absent (Campion and Valenzuela, 2001). In the absence of a credit bureau, group lending ameliorates asymmetric information problems by using the information group members have about each

other and their incentives to screen out bad group members. Janvry et al. (2010) show that the impact of the introduction of a credit bureau confirms the efficacy of group lending in diminishing asymmetric information. As a result of a new credit bureau, the lender's screening ability improves more for individual borrowers than for group borrowers. In addition, solidarity groups become smaller when credit information is available, which suggests that the credit bureau acts as a substitute for information and incentives associated with larger groups. So, MFIs that practice group lending are less dependent on information sharing institutions. Consequently, when there is limited information sharing, there is a larger market for microfinance.

Information sharing agencies play an important role in reducing costly asymmetries in developing countries. Djankov et al. (2007) show that poor countries have a higher incidence of public information sharing agencies than rich ones and that only in poor countries these agencies are associated with more private credit. So when there is more information sharing, formal financial institutions have a competitive advantage to microfinance, which reduces the market for microfinance.

The fourth problem, debt enforcement, is due to a lack of collateral, which group lending solves by making group members jointly responsible for each other's loans. Other microfinance contracts solve this problem by using dynamic incentives, which effectively use lenders' future lending possibilities as today's collateral. For example, when lenders default they are denied future lending. Because microfinance contracts avoid the need for collateral, they are less in need of debt enforcement institutions and creditor rights. In addition, microfinance loans are typically very small, so even if a borrower defaults, the size of a loan does not make it worthwhile to start debt enforcement procedures.

Microfinance avoids many problems associated with inefficient debt enforcement, weak creditor rights and limited information sharing, so it is a substitute for formal, traditional bank lending when institutions are weak. Barriers to efficient, formal firm operation create a larger and more diverse pool of customers for microfinance. The resulting diversification advantages decrease MFI risk.

*Hypothesis 1:* Microfinance is a substitute for formal finance, so barriers to efficient formal firm operation like a lack of creditor rights, limited information sharing and inefficient debt enforcement, decrease MFI risk.

### 6.2.3 The moderating effect of creditor rights and legal origin

Countries in different legal traditions have different strategies of social control of business, which could have different effects on private credit provision and microfinance in particular. Civil law countries—specifically French civil law countries—rely on government regulation and ownership, whereas common law countries rely more on private contracting and enforcement through courts. Accordingly, Djankov et al. (2007) find that civil law countries have relatively many information sharing agencies and low creditor rights, whereas common law countries have higher creditor rights but less information sharing agencies.

Especially poor civil law countries specialize in information sharing to make their credit markets work: 83.3% of the poor French legal origin countries have public information sharing agencies, compared to only 26.3% of the poor common law countries. Because Djankov et al. (2007) also find that information sharing agencies increase private credit provision only in poor countries, these findings suggest that governments of French legal origin countries successfully use public information sharing agencies as a substitute for creditor rights.

The findings of Djankov et al. (2007) imply that the role for microfinance to act as substitute for weak legal institutions is largest in common law countries and countries which have high creditor rights. Civil law countries use government intervention through public information sharing agencies for their credit markets to function. Because their information sharing agencies tackle problems of asymmetric information, the role for microfinance to solve this problem becomes smaller. By contrast, common law countries rely more on intervention by courts to resolve credit conflicts. When debt enforcement is inefficient in common law countries, there is a larger market for microfinance.

*Hypothesis 2:* Inefficient debt enforcement institutions enlarge the microfinance market and decrease risk mostly in common law countries and in countries with high creditor rights.

### 6.2.4 The moderating effect of MFI type

From the substitution hypothesis it follows naturally that MFIs that are the most dissimilar to formal financial institutions form their best substitutes. The landscape of MFIs is very heterogeneous including MFIs with different legal statuses, such as banks, rural banks, non-bank financial institutions (NFBIs), credit unions and non-governmental organizations (NGOs). Of these institutions nonprofits and

unregulated MFIs are most dissimilar to regular financial institutions.

NGOs, credit unions and thirty to forty percent of the NBFIs are nonprofit institutions. Nonprofits typically have dual objectives; their donors want them to alleviate poverty and be financially sustainable. Nonprofits serve the poorest of the poor with the smallest average loan sizes. Their borrowers usually have no collateral, so they use lending techniques that incentivize lenders to repay despite a lack of collateral. In addition, group lending could be a substitute for information sharing, as the information and incentives group members have about each other substitute for the information of a credit bureau (Janvry et al., 2010). For-profit MFIs include (rural) banks and sixty to seventy percent of the NBFIs. They have a clear financial objective, larger loan sizes and typically use individual lending instead of group lending, so they are likely to require more information on creditors.

A typical evolution of an MFI starts with a small nonprofit MFI. As this MFI grows it starts to offer larger loans to successful customers and starts to offer other financial services, sometimes including savings. Due to its growth, it requires more capital, which it can acquire more easily when it obtains a for-profit status and becomes a regulated financial institutions. So regulated MFIs are often, but not always, for-profit MFIs. Because regulated and for-profit MFIs are more akin to formal financial institutions, they are more likely to compete with them. In addition, they are also more likely to make use of debt enforcement institutions and creditor rights, because their loan sizes are larger. Therefore, only nonprofits and unregulated MFIs are likely to be substitutes for regular financial institutions:

*Hypothesis 3:* Inefficient debt enforcement institutions enlarge the microfinance market and decrease risk only for nonprofits and unregulated MFIs.

### 6.2.5 Portfolio growth

A loan portfolio can grow in two ways; loan size growth and borrower growth, which Ahlin et al. (2010) call growth on the intensive and extensive margin, respectively. Ahlin et al. (2010) find that debt enforcement inefficiency is negatively related to loan-size growth and positively to borrower growth, which leads them to suggest that microfinance flourishes as a substitute when institutions are weak. In addition, they find that creditor rights and information sharing are negatively related to loan size growth.

The story that emerges from Ahlin et al. (2010) and the discussion leading to hypothesis 3, is that MFIs initially benefit from inefficient debt enforcement, because their lending contracts can substitute for these institutions. Yet, as MFIs grow and

commercialize they start to offer larger loans, compete more with regular financial institutions and maybe start individual lending instead of group lending. These changes imply that they lose their initial competitive advantage. According to hypothesis 1, microfinance is a substitute for weak institutions and therefore MFIs obtain diversification benefits from a larger microfinance market. To test whether the diversification mechanism drives hypothesis 1, I formulate:

*Hypothesis 4:* Inefficient debt enforcement, creditor rights and information sharing are negatively related to loan-size growth and positively related to borrower growth.

## 6.3 Data and summary statistics

This section first introduces my sample. Second, I discuss my debt enforcement inefficiency, creditor rights and information sharing measures. Third, I introduce the Z-score as a measure of MFI risk. Finally, I discuss my control variables.

### 6.3.1 The sample

For my main specification this study obtains data from four different sources. First, I obtain MFI-level accounting data from MixMarket.<sup>2</sup> All numerical data are converted to US dollars. MFIs can voluntarily participate in the MixMarket database, but data entry is closely monitored by MixMarket. Participants have to enclose documentation that supports the data, such as audited financial statements and annual reports. In order to be able to provide such data, reporting MFIs should have an adequate information infrastructure.

Similar to Ahlin et al. (2010), I collect data on all MFIs that meet certain criteria. First, I include only institutions audited by a third-party accounting firm or similar, to ensure reliability and comparability of the data. Second, I select MFIs that have at least observations for four consecutive years. Third, the four years of data must correspond to a calendar-year fiscal year, to be able to compare it with annual country-level data. Fourth, MFIs should monitor their risk taking, which I proxy by excluding MFIs that do not report portfolio-at-risk. Finally, similar to Houston et al. (2010), I only use recent data reported over the period 2000-2008.

My second source is Djankov et al. (2007) and World Bank "Doing Business" datasets from which I obtain information on creditor rights, information sharing

---

<sup>2</sup> [www.mixmarket.org](http://www.mixmarket.org)

and debt enforcement inefficiency. To control for macroeconomic factors that influence microfinance performance and efficiency my third source is the World Development Indicators (2009) dataset. Finally, I use the banking regulation database compiled by Barth et al. (2006) to control for the effect of bank regulation

### **6.3.2 Debt enforcement inefficiency, creditor rights and information sharing measures**

Djankov et al. (2008) argue that debt enforcement inefficiencies can be attributed to three general causes: long delays, high administrative costs and excessive piecemeal sales of viable businesses. To capture these components of the debt enforcement inefficiency, I use three variables, namely; (1) the time it takes to enforce a contract; (2) the costs involved with enforcing a contract and (3) the recovery rate, respectively. I obtain the first measure, contract enforcement days, from Djankov et al. (2007). This measure is based on the methodology developed in Djankov et al. (2003) and indicates the time it takes to enforce a contract of unpaid debt worth 50% of the country's GDP per capita. Djankov et al. (2003) note that to measure the inefficiency of ordinary persons using the legal system, this duration estimate is highly relevant. My second measure is contract enforcement costs (as % of the claim). My third measure is the recovery rate, which is the percentage of debt that can be recovered after foreclosure. The recovery rate is likely to be lower when the firm cannot be saved as a going concern, but is sold piecemeal instead. I obtain data on contract enforcement costs and the recovery rate from the World Bank Doing Business Dataset.

Table 6.1 reports my measures of debt enforcement inefficiency. My first measure is contract enforcement days, which is the number of days it takes to enforce a contract in terms of hundreds of days. The mean number of contract enforcement days is 445 and the standard deviation is 232 days. Contract enforcement days is very dispersed, ranging from 27 days in Tunisia to 1459 days in Guatemala. Second, the average contract enforcement costs are 36.1% of the claim. This implies that a creditor pays on average \$361 in enforcement costs for a debt contract of \$1000. Third, the average recovery rate is 21.6%, which implies that after business closure, on average 21.6% of the loan amount is recovered.

Table 6.1. Summary Statistics

	Mean	Std.Dev.	Min	Max	Countries	Obs
<i>MFI-level data</i>						
Log Z-score	2.633	0.977	-2.733	5.317	41	311
ROA	0.030	0.058	-0.434	0.232	41	311
CAR	0.368	0.232	0.018	0.957	41	311
$\sigma(\text{ROA})$	0.037	0.044	0.002	0.338	41	311
MFI growth	0.295	0.264	-1.978	1.507	41	311
MFI size	15.967	1.702	11.878	20.965	41	311
Provisions/Assets	0.017	0.018	-0.064	0.115	41	311
PAR30	0.057	0.058	0.000	0.492	41	311
Portfolio growth	0.327	0.182	-0.063	0.978	41	311
Loan size growth	0.110	0.139	-0.736	0.762	41	311
Borrower growth	0.217	0.191	-0.345	1.208	41	311
<i>Country-level data</i>						
Contract enforcement days ( $\times 100$ )	4.452	2.324	0.270	14.590	41	41
Contract enforcement cost	0.361	0.217	0.120	1.103	41	41

Table 6.1. Summary Statistics (continued)

	Mean	Std.Dev.	Min	Max	Countries	Obs
Recovery rate	0.216	0.159	0.000	0.652	41	41
Creditor rights	1.463	1.325	0	4	41	41
Information sharing	0.878	0.331	0	1	41	41
Depth of credit information	2.878	2.124	0	6	41	41
Diversification index	1.268	0.633	0	2	41	41
Overall capital stringency	4.317	1.404	1	7	41	41
Financial statement transparency	4.780	0.759	3	6	41	41
HHI	0.606	0.295	0.083	1	41	41
Log GDP per capita	8.314	0.859	6.655	9.575	41	41
Log GDP	24.956	1.514	22.247	28.127	41	41
Inflation (%)	7.575	4.633	1.291	18.417	41	41

Notes: The 41 countries include Argentina, Azerbaijan, Benin, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Burkina Faso, Cameroon, Chad, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Jordan, Kazakhstan, Kenya, Lebanon, Mali, Mexico, Moldova, Morocco, Nicaragua, Nigeria, Pakistan, Panama, Papua New Guinea, Peru, Philippines, Poland, Romania, Rwanda, Senegal, Sri Lanka, Thailand, Togo, Tunisia, Turkey, Ukraine

Table 6.2. Z-score and creditor rights: MFI level basic OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Contract enforcement days	0.060*** [0.000]	0.056*** [0.000]	0.054*** [0.000]	0.071*** [0.000]	0.065*** [0.000]	0.064*** [0.000]
Contract enforcement cost		-1.032** [0.014]	-0.792* [0.075]		-0.754 [0.107]	-0.512 [0.299]
Recovery rate			-0.463** [0.047]			-0.467* [0.060]
Information sharing	-0.304 [0.171]	-0.240 [0.246]	-0.239 [0.234]			
Creditor rights	0.067 [0.119]	0.013 [0.718]	0.035 [0.339]	0.059 [0.170]	0.021 [0.550]	0.044 [0.233]
Diversification index	-0.114 [0.103]	-0.063 [0.322]	-0.065 [0.260]	-0.120** [0.036]	-0.080 [0.172]	-0.082 [0.110]
Overall capital stringency	-0.029 [0.459]	-0.056 [0.111]	-0.045 [0.174]	-0.036 [0.336]	-0.054 [0.122]	-0.044 [0.193]
Financial statement transparency	0.138 [0.247]	0.175 [0.109]	0.129 [0.210]	0.112 [0.322]	0.142 [0.198]	0.096 [0.370]

Table 6.2. Z-score and creditor rights: MFI level basic OLS regressions (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
MFI size	0.106*** [0.000]	0.111*** [0.000]	0.117*** [0.000]	0.117*** [0.000]	0.118*** [0.000]	0.124*** [0.000]
HHI	-0.732*** [0.000]	-0.618*** [0.001]	-0.676*** [0.000]	-0.920*** [0.000]	-0.796*** [0.000]	-0.856*** [0.000]
MFI growth	-0.577 [0.120]	-0.556 [0.124]	-0.543 [0.128]	-0.620* [0.093]	-0.593 [0.103]	-0.580 [0.106]
Log GDP per capita	0.322*** [0.009]	0.340*** [0.007]	0.370*** [0.005]	0.528*** [0.000]	0.497*** [0.000]	0.528*** [0.000]
Log GDP	-0.065 [0.344]	-0.133* [0.051]	-0.114* [0.090]	-0.072 [0.297]	-0.120* [0.081]	-0.101 [0.138]
Inflation	-0.016 [0.475]	-0.009 [0.669]	-0.013 [0.519]	-0.026 [0.245]	-0.018 [0.412]	-0.022 [0.304]
Depth of credit information				-0.104*** [0.003]	-0.082** [0.048]	-0.082** [0.039]
Constant	-0.040 [0.970]	1.584 [0.111]	0.998 [0.334]	-1.397 [0.180]	0.069 [0.954]	-0.526 [0.669]

Table 6.2. Z-score and creditor rights: MFI level basic OLS regressions (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Observations	311	311	311	311	311	311
Adjusted R-squared	0.111	0.118	0.119	0.122	0.124	0.125
Countries	41	41	41	41	41	41

Notes: This table reports the results of estimating model (1) with OLS. The dependent variable is the logarithm of Z-score.  $Z\text{-score} = (ROA + CAR) / \sigma(ROA)$ , where ROA is the return on assets and CAR is the capital-asset ratio, which are both averaged over 2000-2008.  $\sigma(ROA)$  is the standard deviation of return on assets over 2000-2008. A higher Z-score implies less risk. Heteroskedasticity-robust p-values, clustered by countries are reported in brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

I follow La Porta et al. (1998) and use the creditor rights index to measure the powers of secured creditors in bankruptcy.<sup>3</sup> The index consists of four components. First, whether there are restrictions imposed, such as creditors' consent or minimum dividend, when a debtor files for reorganization. Second, whether secured creditors are able to gain possession of assets after the petition for reorganization is approved. Third, whether secured creditors are ranked first in the distribution of proceeds of liquidating a bankrupt firm as opposed to other creditors. Fourth, whether the incumbent management does not stay in control of the firm during the reorganization. The index ranges from zero to four, where one point is added for each of these creditor rights. The creditor rights index is highly persistent over time, so I take the value of the index in 2003, which is the last year included in the Djankov et al. (2007) dataset that covers annual observations across 129 countries over the period from 1978 to 2003.

The average creditor rights score across countries and years is 1.463, which is markedly lower than the average of 2.018 reported by Houston et al. (2010). The reason is of course that my sample mostly includes developing countries, whereas their sample includes both developed and developing countries. In fact, out of the 41 countries in the sample, 12 have a zero creditor rights score, which represents 112 out of 311 MFIs.

Information sharing is a dummy, which equals one if an information sharing agency (public registry or private bureau) is operating in the country by the end of 2005 and zero otherwise. These agencies maintain databases on the creditworthiness of borrowers in the financial system. Their primary function is to facilitate exchange of information among banks and financial institutions (Djankov et al., 2007). As documented by Djankov et al. (2007), information sharing is very prevalent in my sample of developing countries: 36 countries have a public or private information sharing agency. The depth of credit information index ranges from zero to six, where higher values indicate the availability of more credit information. Even though most countries have an information sharing agency, the average index value of 2.878 is lower than the average depth of credit information reported by Houston et al. (2010), which equals 3.515.

The extent of information collected differs markedly across countries. Some agencies only collect limited information on outstanding loans of large borrowers, while others collect extensive information, such as late payments and defaults, demographic data, credit inquiries and ratings (Djankov et al., 2007). Therefore

---

<sup>3</sup>Djankov et al. (2007) report the caveat that this particular measure of investor protection, in comparison to creditor rights more generally, might be especially relevant to debt finance in the richer countries.

I use the depth of credit information index from the World Bank Doing Business dataset to correct for differences in the extent of information reported across countries. This index measures rules that affect the scope, accessibility and quality of credit information available through public and private credit registries (Houston et al., 2010). The six characteristics include: (1) both positive and negative credit information; (2) data on both firms and individual borrowers are distributed; (3) data from retailers, trade creditors, or utilities, as well as from financial institutions are distributed; (4) more than two years of historical data are distributed; (5) data are collected on all loans of value above 1% of income per capita; and (6) laws are provided for borrowers' rights to inspect their own data. The index ranges from zero to six, where one point is added when a country has one of these characteristics. So higher values indicate the availability of more credit information.

### 6.3.3 Z-score: measuring MFI risk

To measure MFI risk I compute a Z-score for each MFI, which is computed as the return on assets plus the capital-asset ratio divided by the standard deviation of return on assets. That is,  $Z\text{-score} = (ROA + CAR) / \sigma(ROA)$ , where ROA is the return on assets, CAR is the equity-to-assets ratio and  $\sigma(ROA)$  is the standard deviation of return on assets. This measure can be interpreted as the number of standard deviations profits can fall before depleting equity capital (Boyd et al., 2006). In the recent literature the Z-score has been widely used as a measure of a bank's distance to insolvency (e.g. Houston et al., 2010; Laeven and Levine, 2009). Note that insolvency risk is a more specific risk than the variability measures we used as dependent variable in chapter 5.<sup>4</sup> Since the Z-score is highly skewed, I follow the literature by taking the natural logarithm of the Z-score. My dataset includes 311 MFIs, from 41 countries over the period 2000 to 2008 using the Mixmarket database. So the ROA and CAR are calculated as the mean and  $\sigma(ROA)$  is calculated as the standard deviation of ROA, estimated over 2000-2008.

Table 6.1 reports summary statistics. It shows that the mean log Z-score is 2.633 and the standard deviation is 0.977. These summary statistics are similar to those reported by Laeven and Levine (2009), who look at 287 banks across 33 countries and report a mean log Z-score of 2.85 with a standard deviation of 0.99. Houston et al. (2010) look at a much larger sample of 2386 banks across 69 countries and report

---

<sup>4</sup>Note that in the robustness checks in section 6.5.1 we take the standard deviation as dependent variable, like we also do in chapter 5. The primary motivation for choosing specific risk measures in this chapter and chapter 5 is comparability with the literature on insolvency risk, and CEO power and risk, respectively

a mean log Z-score of 3.240 with a standard deviation of 1.086.

### 6.3.4 Bank regulation controls, bank controls and macro controls

Although about half of the MFIs in my sample are not regulated, I control for measures of banking regulation that could affect the regulated half of the sample. In addition, these variables capture the competitive characteristics of the market in which also unregulated MFIs operate. From the banking regulation database compiled by Barth et al. (2006) I include capital stringency, the diversification index and financial statement transparency.

Capital stringency is based on a number of variables that measure whether capital requirements reflect certain risk elements. It takes the minimum capital-asset ratio into account, whether it is in line with the Basel Committee on Banking Supervision guidelines and to what extent it varies as a function of different types of risks. It also takes into account how bank losses affect the book-value of bank capital. The diversification index measures whether there are explicit, verifiable, and quantifiable guidelines regarding asset diversification and whether banks are allowed to make loans abroad. A higher index value implies more bank asset diversification. Financial statement transparency indicates to what extent banks are forced to disclose information. It includes whether accrued, though unpaid, interest/principal enters the income statement while the loan is still performing; whether financial institutions are obliged to produce consolidated accounts covering all bank and any non-bank financial subsidiaries; whether off-balance sheet items are disclosed to the supervisor; whether banks must disclose their risk management procedures to the public; whether bank directors are legally liable if disclosed information is erroneous or misleading and whether regulations require credit ratings for commercial banks.

To control for the effects of market concentration, I use the standard Herfindahl-Hirschman Index (HHI), which equals the sum of the squares of the market shares (in terms of assets) of each individual MFI in individual countries. Although not all MFIs operating in a country report to Mixmarket, HHI is a reasonable proxy for market concentration since worldwide the largest MFIs do report to Mixmarket. The (normalized) HHI ranges from zero to one with a higher value indicating greater monopoly power.

I also control for a number of bank characteristics. I use the natural logarithm of the average MFI size over the period 2000-2008. The square of MFI size is not included, due to the fact that this variable is highly collinear with MFI size. MFI

growth is the average growth rate of MFI financial revenue.

To control for differences in economic development across countries I include several country-level control variables. The natural logarithm of real GDP per capita is included to capture a country's economic development. I include the natural logarithm of real GDP to capture the size of the economy. Finally, I also control for inflation based on a consumer price index.

## 6.4 Results

### 6.4.1 Hypothesis 1: the effect of credit institutions on MFI risk

My first set of analyses considers the effect of debt enforcement inefficiency, creditor rights and information sharing on MFI risk taking. My main dependent variable is the log Z-score. The key independent variables are contract enforcement days, contract enforcement costs and recovery rate, which measure debt enforcement inefficiency, the creditor rights index and two information sharing measures, namely an information sharing dummy, and the depth of credit information index. I run the following regression:

$$\begin{aligned}
 Z_{i,j} = & \alpha + \beta_1 \text{Debt enforcement inefficiency measures}_j \\
 & + \beta_2 \text{Creditor rights measures}_j \\
 & + \beta_3 \text{Information sharing measures}_j \\
 & + \beta_4 \text{Bank regulation controls}_j \\
 & + \beta_5 \text{Bank controls}_{i,j} \\
 & + \beta_6 \text{Macro controls}_j + \epsilon_{i,j}
 \end{aligned}$$

where the  $i$  and  $j$  subscripts indicate bank and country, respectively.  $Z_{i,j}$  is the log Z-score or portfolio growth,  $\alpha$  is a constant and  $\beta_k$  is a vector of parameters. Debt enforcement inefficiency measures include contract enforcement days, contract enforcement costs and recovery rate. The creditor rights measure is based on the aggregate creditor rights index in 2003. Information sharing measures include the information sharing dummy variable and depth of credit information. Bank regulation controls include capital stringency, diversification index, financial transparency and a microfinance HHI index. MFI controls include MFI size and MFI growth. Macro controls include log real GDP per capita, log real GDP and inflation. I take the average of all time-varying independent variables over the period 2000-

2008. Section 6.3 contains a definition of all the variables. I use heteroskedasticity-robust standard errors clustered by country to compute p-values.<sup>5</sup>

Table 6.2 presents the regression results: it shows that higher contract enforcement days are consistently related to less MFI risk while higher recovery rates imply more MFI risk (remember that a higher Z-score implies less risk). So inefficient debt enforcement is associated with less MFI risk, which confirms hypothesis 1. The effect of contract enforcement days is economically significant. A one standard deviation increase in contract enforcement days (232.4 days) is associated with a change in Z-score of about 0.14 ( $0.06 \times 2.324$ ), where the average Z-score is 2.663. A one standard deviation increase in the recovery rate is associated with a 0.07 drop in the Z-score. Contrary to the other two measures, in specification (1)-(3), higher contract enforcement costs are associated with more MFI risk.

I do not find any effect of creditor rights and information sharing on MFI risk. Nonetheless, I do find the depth of credit information significantly increases MFI risk. This confirms hypothesis 1, more information sharing implies that there is less room for microfinance to alleviate asymmetric information problems. A smaller market for microfinance implies less diversification and thus more risk. So I find evidence that information sharing institutions and microfinance are substitutes.

The effect of the depth of credit information is economically significant: a one standard deviation increase in the depth of credit information is associated with a drop in Z-score of about 0.06. Also microfinance market concentration, as measured by HHI, is associated with a very strong and significant increase in MFI risk: a one standard deviation increase in HHI is associated with 0.41 drop in Z-score.<sup>6</sup>

GDP per capita and MFI size are very significant predictors of MFI risk, where more developed countries and larger MFIs are associated with less risk. Larger MFIs have larger loan portfolios and thus more diversification opportunities. Surprisingly, I would expect GDP per capita to be associated with more MFI risk, because higher GDP per capita implies a smaller microfinance market.

In comparison to Houston et al. (2010), bank regulatory variables do not have a very significant impact on MFI risk, which could reflect the fact that more than half of the MFIs are not regulated. Also inflation does not have an effect on MFI risk, which could be due to the fact that microfinance borrowers operate in the informal sector, which is relatively shielded from the rest of the economy.

---

<sup>5</sup> Clustering standard errors by country implies that I allow correlation within countries, but not between countries. Beck, Demirgüç-Kunt and Peria (2007), amongst others, show that clustering standard errors by country gives robust and reliable standard errors.

<sup>6</sup> Note, however, that I do not have information on all MFIs in a country, such that a market concentration measure like HHI could be biased upward.

## 6.4.2 Hypothesis 2: the moderating effect of creditor rights and legal origin

Next, I investigate the interaction between debt enforcement inefficiency and creditor rights. There are two major categories of legal traditions, namely common law and civil law. Civil law countries focus more on information sharing and less on enforcement of creditor rights. By contrast, common law countries have higher creditor rights which are more actively enforced through courts, although they make less use of information sharing agencies. Therefore, according to hypothesis 2 microfinance is more likely to be a substitute for inefficient debt enforcement in common law countries and countries with high creditor rights.

The first column of Table 6.3 presents the results of including an interaction between contract enforcement days and creditor rights. The interaction term is positive and significant, while the main effect of contract enforcement days is no longer significant. This confirms hypothesis 2: in countries with high creditor rights the microfinance market is larger and therefore gives MFIs more diversification opportunities. Figure 6.1 present a plot of the marginal effect of contract enforcement days on the Z-score for different levels of creditor rights, together with a dashed 95% pointwise confidence bound. It shows that in countries with no creditor rights contract enforcement days has no marginal effect on the Z-score, while it has a positive and increasing effect for higher levels of creditor rights.

To test this explanation further, I split the sample into MFIs in countries with creditor rights (Creditor rights  $> 0$ ) and countries with no creditor rights (Creditor rights = 0). Table 6.3 presents the results of the split-sample specifications in columns 5 and 6, respectively. They provide evidence that contract enforcement days decrease MFI risk in countries that have creditor rights, but increases MFI risk in countries that do not have creditor rights. The increase of MFI risk in countries with zero creditor rights is pronounced; a one standard deviation increase in the number of days (which is 4.239 in this sample) is associated with a decrease in the Z-score of 3.755, where the average Z-score is 2.471 in this sample.

Also the recovery rate and contract enforcement costs tend to have a more extreme impact in this sample. Possibly this is due to the fact that the 12 countries in this subsample (Benin, Burkina Faso, Cameroon, Chad, Colombia, Ecuador, Mali, Mexico, Peru, Senegal, Togo and Tunisia) include several low-developed countries.

Table 6.3. The interaction of creditor rights and contract enforcement days

	TS	TS	TS	CR>0	CR=0
Creditor rights	-0.075 [0.282]	-0.001 [0.982]	0.006 [0.876]		
Contract enforcement days	0.019 [0.541]	0.058*** [0.000]	0.178*** [0.002]	0.066*** [0.001]	-0.484*** [0.000]
English legal origin		-0.368 [0.444]			
Contract enforcement days × English legal origin		0.212** [0.048]			
Contract enforcement cost	-0.642 [0.207]	-0.513 [0.286]	-0.540 [0.262]	-0.338 [0.687]	-0.815*** [0.000]
Recovery rate	-0.452* [0.074]	-0.723** [0.027]	-0.614** [0.014]	-0.712 [0.280]	-7.122*** [0.000]
Depth of credit information	-0.072* [0.058]	-0.098** [0.013]	-0.059 [0.113]	-0.123** [0.033]	-0.457*** [0.000]
Diversification index	-0.045 [0.469]	-0.063 [0.178]	-0.086* [0.068]	-0.090 [0.172]	-0.228*** [0.004]

Table 6.3. The interaction of Creditor rights and Contract enforcement days (continued)

	TS	TS	TS	CR>0	CR=0
Overall capital stringency	-0.044 [0.174]	-0.071* [0.051]	-0.053* [0.081]	-0.067 [0.187]	-0.591*** [0.000]
Financial statement transparency	0.077 [0.482]	0.070 [0.452]	0.086 [0.401]	0.024 [0.845]	3.318*** [0.000]
MFI size	0.124*** [0.000]	0.125*** [0.000]	0.124*** [0.000]	0.168*** [0.002]	0.043 [0.242]
HHI	-0.874*** [0.000]	-1.055*** [0.000]	-0.958*** [0.000]	-0.725*** [0.004]	0.292 [0.113]
MFI growth	-0.571 [0.114]	-0.586 [0.102]	-0.587 [0.106]	-0.631 [0.126]	-0.113 [0.890]
Log GDP per capita	0.508*** [0.001]	0.703*** [0.000]	0.502*** [0.001]	0.558*** [0.001]	0.404 [0.135]
Log GDP	-0.123* [0.071]	-0.165** [0.018]	-0.122* [0.051]	-0.111 [0.277]	1.224*** [0.000]
Inflation	-0.021 [0.324]	-0.032 [0.120]	-0.022 [0.281]	-0.04 [0.169]	-0.129*** [0.001]

Table 6.3. The interaction of Creditor rights and Contract enforcement days (continued)

	TS	TS	TS	CR>0	CR=0
Creditor rights	0.032*				
× Contract enforcement days	[0.071]				
French legal origin			0.241		
			[0.296]		
Contract enforcement days			-0.123**		
× French legal origin			[0.020]		
Constant	0.438	0.125	0.132	-0.416	-38.577***
	[0.746]	[0.904]	[0.909]	[0.861]	[0.000]
Observations	311	311	311	199	112
Adjusted R-squared	0.125	0.127	0.126	0.119	0.084
Countries	41	41	41	29	12

Notes: This table reports the results of estimating model (1) with OLS. The dependent variable is the logarithm of Z-score.  $Z\text{-score} = (ROA + CAR) / \sigma(ROA)$ , where ROA is the return on assets and CAR is the capital-asset ratio, which are both averaged over 2000-2008.  $\sigma(ROA)$  is the standard deviation of return on assets over 2000-2008. A higher Z-score implies less risk. CR>0 indicates the subsample of countries that have creditor rights. CR = 0 indicates the subsample that has no creditor rights. Heteroskedasticity-robust p-values, clustered by countries are reported in brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

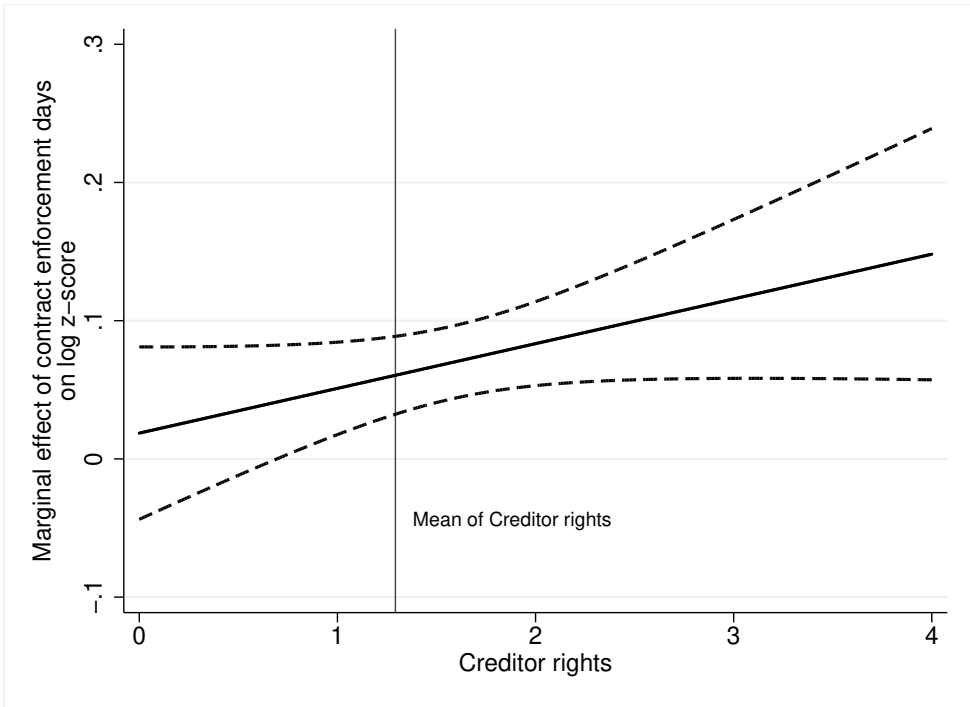


Figure 6.1. The marginal effect of contract enforcement days on MFI risk. The dashed line indicates a 95% pointwise confidence interval

Next, I investigate the interaction between debt enforcement inefficiency and legal origin. My creditor rights measure might be especially relevant to debt finance in the richer countries. Therefore, legal origin could be a better proxy for whether countries primarily use information sharing or enforcement through courts for the functioning of their credit market. I interact contract enforcement days with French legal origin (civil law) and English legal origin (common law). Column 2 and 3 of Table 6.3 show that contract enforcement days are associated with less MFI risk in countries with English legal origin, which confirms Hypothesis 2. By contrast, they are associated with more MFI risk in countries with a French legal origin. This is consistent with French legal origin countries using more information sharing, which gives MFIs a competitive disadvantage relative to formal financial institutions.

### 6.4.3 Hypothesis 3: the moderating effect of MFI type

MFIs that are the most dissimilar to formal financial institutions form their best substitutes. These nonprofit and unregulated institutions cater to the poorest of the

poor, for which specialized microfinance contracts like group lending are used to avoid problems of a lack of information and inadequate collateral.

Table 6.4. Z-score by profit status and regulation

	(1)	(2)	(3)	(4)
<b>Panel A: profit status</b>	NP	P	NP	P
Contract enforcement days	0.069*** [0.001]	0.008 [0.908]	0.075*** [0.001]	0.006 [0.937]
Contract enforcement cost	-0.401 [0.425]	-2.400*** [0.004]	-0.039 [0.945]	-2.167** [0.014]
Recovery rate	0.361 [0.445]	0.305 [0.684]	0.200 [0.673]	0.118 [0.889]
Information sharing	-0.386* [0.066]	-0.567 [0.138]		
Creditor rights	0.007 [0.915]	0.121 [0.347]	0.023 [0.703]	0.105 [0.510]
Diversification index	-0.258*** [0.001]	0.336 [0.132]	-0.256*** [0.001]	0.389* [0.059]
Overall capital stringency	0.022 [0.676]	-0.209** [0.049]	0.023 [0.656]	-0.195* [0.089]
Financial statement transparency	0.101 [0.527]	0.245 [0.335]	0.018 [0.910]	0.160 [0.501]
MFI size	0.177*** [0.000]	0.178* [0.056]	0.178*** [0.000]	0.167* [0.076]
HHI	-0.260 [0.415]	-1.026** [0.016]	-0.528 [0.129]	-0.994*** [0.009]
MFI growth	-0.299 [0.517]	-0.839** [0.011]	-0.328 [0.482]	-0.767** [0.016]
Log GDP per capita	0.481*** [0.004]	0.293 [0.413]	0.662*** [0.000]	0.297 [0.388]
Log GDP	-0.242***	0.094	-0.218**	0.073

Table 6.4. Z-score by profit status and regulation (continued)

	[0.010]	[0.622]	[0.015]	[0.702]
Inflation	-0.014	-0.024	-0.020	0.002
	[0.593]	[0.479]	[0.458]	[0.972]
Depth of credit information			-0.089**	-0.012
			[0.041]	[0.919]
Constant	1.984	-4.255	0.218	-3.959
	[0.198]	[0.325]	[0.897]	[0.312]
Observations	207	104	207	104
Adjusted R-squared	0.164	0.27	0.167	0.259
Countries	36	25	36	25
<hr/>				
<b>Panel B: Regulation</b>	UR	R	UR	R
Contract enforcement days	0.108***	-0.048	0.119***	-0.035
	[0.000]	[0.444]	[0.000]	[0.576]
Contract enforcement cost	-0.256	-0.924*	-0.129	-0.637
	[0.873]	[0.087]	[0.933]	[0.275]
Recovery rate	0.719	-0.455	0.598	-0.371
	[0.284]	[0.294]	[0.365]	[0.412]
Information sharing	-1.329***	-0.261		
	[0.008]	[0.280]		
Creditor rights	0.305**	-0.009	0.345***	-0.006
	[0.018]	[0.892]	[0.006]	[0.930]
Diversification index	-0.516***	0.024	-0.461***	0.010
	[0.001]	[0.862]	[0.002]	[0.935]
Overall capital stringency	0.179**	-0.132**	0.160**	-0.130**
	[0.037]	[0.027]	[0.038]	[0.027]
Financial statement transparency	0.328	0.103	0.178	0.069
	[0.131]	[0.586]	[0.406]	[0.711]
MFI size	0.206***	0.081	0.198***	0.090*

Table 6.4. Z-score by profit status and regulation (continued)

	[0.000]	[0.109]	[0.000]	[0.079]
HHI	-1.983 <sup>***</sup>	-0.960 <sup>***</sup>	-2.494 <sup>***</sup>	-1.139 <sup>***</sup>
	[0.000]	[0.001]	[0.000]	[0.000]
MFI growth	-0.434	-0.515	-0.466	-0.550
	[0.349]	[0.434]	[0.324]	[0.394]
Log GDP per capita	1.250 <sup>***</sup>	0.123	1.682 <sup>***</sup>	0.296
	[0.000]	[0.328]	[0.000]	[0.109]
Log GDP	-0.257 <sup>*</sup>	-0.013	-0.213	0.004
	[0.099]	[0.862]	[0.139]	[0.960]
Inflation	-0.052	-0.010	-0.047	-0.021
	[0.172]	[0.652]	[0.200]	[0.387]
Depth of credit information			-0.167 <sup>***</sup>	-0.096
			[0.006]	[0.101]
Constant	-5.026	2.116	-9.567 <sup>**</sup>	0.366
	[0.156]	[0.173]	[0.011]	[0.850]
Observations	149	160	149	160
Adjusted R-squared	0.192	0.202	0.198	0.209
Countries	25	33	25	33

Notes: This table reports the results of estimating model (1) with OLS. The dependent variable is the logarithm of Z-score.  $Z\text{-score} = (\text{ROA} + \text{CAR})/\sigma(\text{ROA})$ , where ROA is the return on assets and CAR is the capital-asset ratio, which are both averaged over 2000-2008.  $\sigma(\text{ROA})$  is the standard deviation of return on assets over 2000-2008. A higher Z-score implies less risk. For-profit (P) indicates the subsample of (rural) banks and nonprofit (NP) indicates all other MFIs. Regulated (R) and unregulated (UR) indicates the subsamples regulated by the central bank or not, respectively. Heteroskedasticity-robust p-values, clustered by countries are reported in brackets. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 6.4 tests whether the effect of the quality of debt enforcement differs by running the baseline regressions in Table 2 for subsamples of for-profits, nonprofits, and regulated and unregulated MFIs. The results show that contract enforcement days decreases the risk of for nonprofits and unregulated MFIs, while it has no effect for for-profit and regulated MFIs. The economic significance is comparable

to that found in the baseline regressions in Table 6.2.

If there is an effect of the quality of debt enforcement on for-profit MFIs, the results suggest that it increases instead of decreases risk, since an increase in contract enforcement costs leads to a significant increase in for-profits' risk. The economic effect is very large: a one standard deviation increase in contract enforcement costs (0.217) leads to a drop in Z-score of about 2, where the average Z-score is 2.663. It appears that contract enforcement days are especially relevant for non-profit risk, while contract enforcement costs are more relevant for for-profit risk. This could also explain why I find opposite effects of contract enforcement days and contract enforcement costs in my total sample.

#### **6.4.4 Hypothesis 4: the effect of credit institutions on portfolio growth**

The previous results have shown that inefficient debt enforcement decreases MFI risk, because inefficient debt enforcement increases the market for microfinance. Therefore, I expect a positive relation between debt enforcement inefficiency and portfolio growth.

The total loan portfolio is the number of borrowers multiplied by the average loan size, so growth can result from an increase in the number of borrowers or an increase of the average loan size. I will refer to these as borrower growth and loan size growth. Since I use log growth, borrower growth and loan size growth exactly add up to portfolio growth. As debt enforcement becomes less efficient, it becomes increasingly less efficient for formal financial institutions to offer smaller loans. Consequently, inefficient debt enforcement leads to a larger market for microfinance and thus to higher borrower growth, a result also found by Ahlin et al. (2010). By contrast, inefficient debt enforcement impairs loan-size growth, because larger microfinance loans eventually require the use of debt enforcement institutions.

Table 6.5 presents the results of regressing portfolio, borrower and loan-size growth on the set of explanatory variables. It shows that contract enforcement days is not related to borrower growth, but it is negatively related to loan-size growth, which confirms the conjecture that micro-lenders fail to graduate to larger loans when debt enforcement is inefficient. The relation between contract enforcement days and loan size growth is economically significant: an increase in contract enforcement days with one standard deviation (232.4 days) is associated with a drop in loan-size growth of 1.16% ( $0.005 \times 2.324$ ), where the average loan size growth is

11%.

Table 6.5 also shows that the depth of credit information negatively affects portfolio growth and loan size growth. This is again consistent with the competition argument: MFIs have a competitive disadvantage with respect to regular banks that do have access to credit information, which leads to less portfolio growth. Table 6.5 also shows evidence that market concentration with the microfinance sector (HHI) is positively related to portfolio and borrower growth. Possibly there is a reverse effect: microfinance growth leads to consolidation within the microfinance sector.

Finally, the recovery rate is positively related to portfolio growth, which appears to be due to the positive effect of the recovery rate on borrower growth. So better repayment is associated with an increasing number of poor borrowers receiving a loan. An increase in recovery rate with one standard deviation (0.159) is associated with an increase in borrower growth of 3.8% ( $0.240 \times 0.159$ ), where average borrower growth is 21.7%.

## 6.5 Robustness checks

In this section I perform several robustness checks on the results found for the main specification in Table 6.2. To find out which of the components of the Z-score is mainly responsible for the relationship between the legal variables and MFI risk I use ROA, CAR and  $\sigma(\text{ROA})$  as separate independent variables in section 6.5.1. As additional robustness test, I measure risk by the ratio of provisions for loan impairment over assets and portfolio-at-risk 30 days ratio, which is the fraction of the portfolio that is more than 30 days overdue. To check whether my results are driven by a subsample of countries or MFIs, I perform weighted regressions and country level regressions in section 6.5.2.

### 6.5.1 Z-score disaggregation and alternative MFI risk measures

The Z-score equals the ratio of ROA plus CAR to the standard deviation of ROA. So an increase in Z-score, which is a decrease in risk, could be due to an increase in ROA or CAR, or due to a decrease in the standard deviation of ROA. So it is possible that contract enforcement days only lead to, for instance, an increase in the capital-asset ratio and not necessarily to a decrease in risk. To find out how creditor rights, information sharing and quality of law enforcement influence different components of the Z-score, I run regressions treating each of the Z-score components as a separate dependent variable.

Table 6.5. : The effect of debt enforcement quality on portfolio growth, borrower growth and loan-size growth

	(1)	(2)	(3)	(4)	(5)	(6)
	portfolio	portfolio	borrower	borrower	loan size	loan size
	growth	growth	growth	growth	growth	growth
Contract enforcement days	-0.003 [0.299]	-0.002 [0.582]	0.004 [0.280]	0.003 [0.440]	-0.006*** [0.005]	-0.004* [0.073]
Contract enforcement cost	-0.160 [0.159]	-0.100 [0.412]	-0.050 [0.733]	-0.048 [0.772]	-0.092 [0.450]	-0.030 [0.813]
Recovery rate	0.167* [0.067]	0.165* [0.052]	0.240*** [0.003]	0.240*** [0.004]	-0.062 [0.399]	-0.063 [0.315]
Information sharing	-0.129** [0.020]		-0.081 [0.200]		-0.053 [0.159]	
Creditor rights	-0.015 [0.291]	-0.013 [0.344]	0.005 [0.748]	0.005 [0.744]	-0.014 [0.199]	-0.012 [0.218]
Diversification index	-0.032 [0.106]	-0.031 [0.138]	-0.027 [0.243]	-0.022 [0.391]	-0.002 [0.926]	-0.006 [0.709]
Overall capital stringency	0.029** [0.026]	0.030** [0.018]	0.025** [0.042]	0.025** [0.039]	0.004 [0.600]	0.004 [0.587]

Table 6.5. : The effect of debt enforcement quality on portfolio growth, borrower growth and loan (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Financial statement	0.017	0.000	0.029	0.019	-0.011	-0.018
transparency	[0.576]	[0.995]	[0.294]	[0.512]	[0.583]	[0.262]
MFI size	0.004	0.005	0.001	0.001	0.004	0.005
	[0.472]	[0.349]	[0.859]	[0.864]	[0.573]	[0.417]
HHI	0.102*	0.056	0.102*	0.094	0.007	-0.034
	[0.062]	[0.406]	[0.079]	[0.210]	[0.846]	[0.276]
Log GDP per capita	-0.036	0.007	-0.043	-0.033	0.002	0.038*
	[0.191]	[0.818]	[0.120]	[0.318]	[0.920]	[0.097]
Log GDP	-0.001	0.002	0.004	0.005	-0.002	0.001
	[0.966]	[0.927]	[0.785]	[0.794]	[0.888]	[0.948]
Inflation	0.005	0.005	0.000	0.002	0.005	0.002
	[0.355]	[0.361]	[0.967]	[0.680]	[0.130]	[0.452]
Depth of credit information		-0.022*		-0.005		-0.018**
		[0.052]		[0.683]		[0.017]
Constant	0.506	0.082	0.202	0.090	0.222	-0.115
	[0.157]	[0.836]	[0.589]	[0.831]	[0.526]	[0.702]

Table 6.5. : The effect of debt enforcement quality on portfolio growth, borrower growth and loan (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Observations	311	311	311	311	311	311
Adjusted R-squared	0.122	0.121	0.044	0.038	0.036	0.052
Countries	41	41	41	41	41	41

Notes: This table reports the results of estimating model (1) with OLS. The dependent variable is portfolio growth, which is the log growth of the gross loan portfolio. Portfolio growth = borrower growth + loan size growth, where borrower growth is growth in the number of borrowers and loan size growth is the growth in average loan size. All variables are averaged over 2000-2008. Heteroskedasticity-robust p-values, clustered by countries are reported in brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 6.A.1 in Appendix 6.A presents the results. It shows that contract enforcement days is significantly associated with a lower standard deviation of ROA. Contract enforcement days does not have an effect on ROA performance and there is some evidence that it positively affects capital asset ratios. Interestingly, the negative impact of depth of credit information on Z-score is due to its negative effect on ROA and capital asset ratios, while it does not have an effect on standard deviation of ROA. This corroborates my assertion that access to information sharing places non-microfinance banks at a competitive advantage vis-à-vis MFIs. Since MFIs do not have access to information sharing, information sharing reduces their ROA performance and their ability to attract equity capital. Market concentration also increases risk. Table 6.A.1 shows that HHI increases the standard deviation of ROA and reduces ROA, thereby reducing the Z-score.

As a robustness check, I also take alternative risk measures as dependent variable. First, I use the raw (no natural logarithm) Z-score as a dependent variable. This allows me to also include 7 observations that were dropped from the sample since they had a negative Z-score. The results are basically similar to those found with the log Z-score measure, with the exception of a very negative significant coefficient on the information sharing dummy. Similar to the finding of a negative effect of depth of credit information, I interpret this result as a competition effect. MFIs have an informational disadvantage compared to banks, such that they end up with a more risky loan portfolio.

In addition, I use the ratio of provision for loan impairment over assets (provisions) and the fraction of the loan portfolio that is more than 30 days overdue (PAR30) as dependent variables. Here I find that contract enforcement days is negatively associated with provisions for loan impairment, while depth of credit information is positively associated with provisions. When contract enforcement days increase, MFI risk decreases and thus they need less provisions. When credit information increases, they face more risk and need more provisions. Surprisingly, PAR30 is positively associated with contract enforcement days, which contradicts my previous results.

## 6.5.2 Robustness checks: weighted regressions and country level regressions

Microfinance has been very successful in some countries, as seen by rapid development of the microfinance sector in these countries. This also implies that some countries have many MFIs, including several very large ones, while other countries

have a much smaller microfinance sector. Therefore, my results could be driven by a subset of large MFIs in a small number of countries. To some extent this problem is tackled by using heteroskasticity robust standard errors, clustered by country. To further control for the uneven distribution of MFIs across countries, I perform two additional robustness checks.

First, I perform weighted OLS regressions, using bank assets as weights. Compared to previous regressions, the results of these analyses are more influenced by the small MFIs in the sample. Table 6.A.2 in Appendix 6.A confirms my main results that contract enforcement days decreases MFI risk and depth of credit information increases MFI risk. The coefficients are even somewhat larger, which suggests that the effects I find are less pronounced for large MFIs. I do find evidence of a positive result of creditor rights in these regressions, which implies that smaller MFIs take less risk as a result of a better creditor rights situation. These results are again consistent with microfinance being a substitute for formal finance. The results of Houston et al. (2010) support this interpretation, because they find the opposite: better creditor rights increase bank risk.

A second robustness check consists of estimating country level regressions in which one country risk measure is regressed on average country explanatory variables. This significantly reduces the sample. Consequently, the results in Table 6.A.3 are a lot less significant. Still, my main results on contract enforcement days and depth of credit information appear to be robust. Contract enforcement days is positively related to the Z-score with coefficients similar to those found in Table 6.2. Depth of credit information is negatively related to the Z-score.

## 6.6 Conclusion

There is a voluminous theoretical literature that deals with finding efficient microfinance contracts (e.g. Ghatak and Guinnane, 1999; Gangopadhyay, Ghatak and Lensink, 2005). In addition, an exciting body of research has emerged that tests the predictions from theoretical microfinance models in randomized control trials (for an overview see for example Banerjee and Duflo, 2010). Both theoretical literature and empirical testing of microfinance contracts deal with debt enforcement from the perspective of finding optimal microfinance contracts. This chapter provides a different perspective; instead of looking at debt enforcement from a contracting perspective, it looks at debt enforcement from an institutional perspective. As such, it falls within a large literature that shows how the credit institutions are important

determinants of credit provision and bank risk.

To my knowledge, this chapter is the first that investigates whether credit institutions affect microfinance risk. The broad conclusion that emerges is that inefficient debt enforcement reduces microfinance risk. From a normative perspective, it is difficult to indicate whether this good or bad. On the one hand, inefficient debt enforcement impedes loan-size growth, which limits the development of the microfinance sector and the ability of borrowers to graduate to larger loans to expand their business. On the other hand, when bad institutions limit formal finance by making it more risky, there is at least a viable alternative in the form of microfinance. These results echo those of Houston et al. (2010) who find evidence of both a "bright" side and a "dark" side to stronger creditor rights. Stronger creditor rights promote greater risk-taking and are correlated to higher growth, even though they also increase the likelihood of a country experiencing a financial crisis.

Although it could be difficult to change the way in which countries administer their debt enforcement procedures, there is reason to be optimistic. Research related to the Doing Business project of the World Bank ([www.doingbusiness.org](http://www.doingbusiness.org)), resulted in great simplifications of business regulations and their enforcement. Between June 2008 through May 2009 287 reforms in 131 economies were introduced in which reformers simplified business regulations, strengthened property rights, eased tax burdens, improved access to credit and reduced the cost of exporting and importing.

Many developing countries use credit information sharing for the functioning of their credit markets. Unfortunately, in many countries microfinance information sharing is still in its infancy (Campion and Valenzuela, 2001). Often public credit bureaus are unavailable to unregulated MFIs and non-profit MFIs believe their clients will not be listed by private bureaus or complain that private bureaus are too costly. In addition, some believe that their best clients might be "stolen" by banks if their good repayment data would be shared in a credit bureau. Currently, most MFIs do not participate in information sharing, which places them at a competitive disadvantage. In countries where there is information sharing and larger depth of credit information, MFI portfolio growth tends to be lower and risk tends to be higher. An interesting future avenue of research would be to directly assess whether regular banks that have access to information sharing institutions have a competitive advantage compared to MFIs that do not have access.

## **6.A Appendix**

### **6.A.1 Appendix A.1**

See Table 6.A.1

### **6.A.2 Appendix A.2**

See Table 6.A.2

Table 6.A.1. Cross-section OLS regressions: ROA and CAR and alternative risk measures

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROA	CAR	CAR	$\sigma(\text{ROA})$	$\sigma(\text{ROA})$
Contract enforcement days	0.001 [0.684]	0.002 [0.266]	0.006 [0.236]	0.011** [0.043]	-0.002** [0.028]	-0.002** [0.033]
Contract enforcement cost	-0.061 [0.278]	-0.035 [0.534]	-0.002 [0.987]	0.128 [0.377]	0.014 [0.591]	0.010 [0.770]
Recovery rate	0.043 [0.181]	0.043 [0.175]	0.149 [0.315]	0.148 [0.233]	0.019 [0.279]	0.020 [0.295]
Information sharing	-0.007 [0.753]		-0.064 [0.264]		0.012 [0.381]	
Creditor rights	0.003 [0.429]	0.004 [0.325]	0.010 [0.532]	0.014 [0.325]	0.002 [0.481]	0.002 [0.532]
Diversification index	-0.005 [0.480]	-0.007 [0.229]	-0.054** [0.029]	-0.066*** [0.005]	0.000 [0.999]	0.000 [0.915]
Overall capital stringency	0.004 [0.367]	0.004 [0.353]	0.011 [0.313]	0.012 [0.304]	0.002 [0.632]	0.001 [0.646]

Table 6.A.1. ROA, CAR and other risk measures (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Financial statement	-0.004	-0.005	-0.021	-0.031	-0.006	-0.005
transparency	[0.695]	[0.596]	[0.509]	[0.280]	[0.398]	[0.572]
MFI size	0.001	0.001	-0.054 <sup>***</sup>	-0.050 <sup>***</sup>	-0.010 <sup>***</sup>	-0.010 <sup>***</sup>
	[0.795]	[0.562]	[0.000]	[0.000]	[0.000]	[0.000]
HHI	-0.052 <sup>**</sup>	-0.067 <sup>**</sup>	0.104	0.025	0.032 <sup>**</sup>	0.036 <sup>*</sup>
	[0.019]	[0.013]	[0.172]	[0.755]	[0.030]	[0.086]
MFI growth	0.009	0.004	-0.020	-0.041	0.031	0.030
	[0.633]	[0.831]	[0.715]	[0.470]	[0.162]	[0.169]
Log GDP per capita	0.001	0.014	0.045 <sup>*</sup>	0.114 <sup>***</sup>	-0.009	-0.013 <sup>*</sup>
	[0.950]	[0.375]	[0.080]	[0.005]	[0.128]	[0.061]
Log GDP	0.001	0.002	-0.003	0.003	0.006	0.006
	[0.905]	[0.769]	[0.879]	[0.887]	[0.118]	[0.145]
Inflation	-0.001	-0.003	-0.008	-0.014 <sup>**</sup>	0.001	0.000
	[0.409]	[0.153]	[0.155]	[0.024]	[0.709]	[0.806]
Depth of credit information		-0.007 <sup>*</sup>		-0.035 <sup>**</sup>		0.002
		[0.071]		[0.013]		[0.625]
Constant	0.032	-0.089	1.056 <sup>**</sup>	0.406	0.109 <sup>*</sup>	0.141 <sup>*</sup>

Table 6.A.1. ROA, CAR and other risk measures (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	[0.798]	[0.495]	[0.018]	[0.303]	[0.072]	[0.077]
Observations	311	311	311	311	311	311
Adjusted R-squared	0.062	0.077	0.208	0.232	0.206	0.082
Countries	41	41	41	41	41	41
<hr/>						
Panel B: Alternative risk measures	Raw Z	Raw Z	Provisions	Provisions	PAR30	PAR30
Contract enforcement days	0.923**	1.114**	-0.001***	-0.001***	0.003**	0.003**
	[0.027]	[0.025]	[0.004]	[0.001]	[0.010]	[0.027]
Contract enforcement cost	-14.953	-7.982	0.018**	0.009	0.066**	0.058*
	[0.124]	[0.412]	[0.022]	[0.257]	[0.046]	[0.082]
Recovery rate	-13.489**	-13.331**	-0.010*	-0.010	-0.015	-0.015
	[0.026]	[0.043]	[0.084]	[0.135]	[0.527]	[0.509]
Information sharing	-13.171***		0.016***		0.001	
	[0.003]		[0.001]		[0.933]	
Creditor rights	0.642	0.850	0.001	0.001	0.004	0.004
	[0.570]	[0.446]	[0.200]	[0.356]	[0.206]	[0.236]
Diversification index	-0.550	-0.613	0.002	0.002	-0.001	0.000

Table 6.A.1. ROA, CAR and other risk measures (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	[0.727]	[0.715]	[0.208]	[0.198]	[0.803]	[0.937]
Overall capital stringency	-1.826**	-1.770**	0.002***	0.002***	-0.002	-0.002
	[0.019]	[0.033]	[0.000]	[0.001]	[0.506]	[0.514]
Financial statement transparency	4.037	2.412	-0.007***	-0.005***	0.003	0.004
	[0.101]	[0.321]	[0.000]	[0.001]	[0.579]	[0.481]
MFI size	0.878	1.017	0.000	0.000	-0.004**	-0.004**
	[0.230]	[0.174]	[0.719]	[0.936]	[0.038]	[0.027]
HHI	-3.183	-8.555	-0.011***	-0.005	0.003	0.008
	[0.557]	[0.149]	[0.001]	[0.152]	[0.802]	[0.488]
MFI growth	-19.877	-20.078	0.013*	0.013*	-0.089***	-0.088***
	[0.157]	[0.151]	[0.062]	[0.052]	[0.007]	[0.008]
Log GDP per capita	7.546**	12.508**	-0.001	-0.007***	-0.019***	-0.024***
	[0.019]	[0.001]	[0.469]	[0.004]	[0.009]	[0.008]
Log GDP	-2.918*	-2.578	0.004***	0.003***	0.013***	0.013***
	[0.074]	[0.098]	[0.000]	[0.001]	[0.003]	[0.004]
Inflation	-0.489	-0.537	0.000	0.000	0.000	0.001
	[0.306]	[0.254]	[0.663]	[0.543]	[0.838]	[0.546]

Table 6.A.1. ROA, CAR and other risk measures (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Depth of credit information		-2.577***		0.003***		0.002
		[0.004]		[0.000]		[0.356]
Constant	31.906	-16.726	-0.063**	-0.007	-0.070	-0.031
	[0.225]	[0.601]	[0.011]	[0.826]	[0.354]	[0.689]
Observations	318	318	311	311	311	311
Adjusted R-squared	0.084	0.088	0.082	0.086	0.246	0.248
Countries	41	41	41	41	41	41

Notes: This table reports the results of estimating model (1) with OLS for the dependent variables indicated in the top row. ROA is the return on assets and CAR is the capital-asset ratio, which are both averaged over 2000-2008.  $\sigma(\text{ROA})$  is the standard deviation of return on assets over 2000-2008. Raw Z, indicates Z-score without taking a logarithm. Provisions is the ratio of impairment loss to assets. PAR30 is the portfolio-at-risk 30 days ratio. Raw Z-score, provisions and PAR30 are averaged over 2000-2008. Heteroskedasticity-robust p-values, clustered by countries are reported in brackets. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 6.A.2. Asset-weighted results

	(1)	(2)	(3)	(4)	(5)	(6)
Contract enforcement days	0.099*** [0.000]	0.100*** [0.000]	0.101*** [0.000]	0.123*** [0.000]	0.116*** [0.001]	0.118*** [0.001]
Contract enforcement cost		-1.720** [0.023]	-1.812** [0.026]		-1.238** [0.042]	-1.334** [0.045]
Recovery rate			0.151 [0.596]			0.182 [0.490]
Information sharing	-0.124 [0.626]	-0.209 [0.400]	-0.226 [0.345]			
Creditor rights	0.126** [0.015]	0.071 [0.132]	0.063 [0.177]	0.130*** [0.004]	0.087** [0.042]	0.076* [0.077]
Diversification index	-0.157 [0.136]	-0.059 [0.549]	-0.056 [0.567]	-0.116 [0.270]	-0.053 [0.605]	-0.050 [0.626]
Overall capital stringency	-0.04 [0.414]	-0.069 [0.195]	-0.075 [0.160]	-0.044 [0.363]	-0.063 [0.217]	-0.071 [0.184]
Financial statement transparency	0.301* [0.097]	0.370** [0.030]	0.391** [0.028]	0.179 [0.217]	0.253* [0.063]	0.275* [0.056]

Table 6.A.2. Asset-weighted results (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
MFI size	0.05 [0.212]	0.056 [0.149]	0.053 [0.189]	0.054 [0.143]	0.058 [0.109]	0.055 [0.137]
HHI	-0.058 [0.880]	-0.013 [0.972]	-0.009 [0.980]	-0.496 [0.122]	-0.368 [0.248]	-0.371 [0.240]
MFI growth	-0.48 [0.403]	-0.601 [0.300]	-0.613 [0.289]	-0.846 [0.192]	-0.821 [0.198]	-0.835 [0.193]
Log GDP per capita	0.379 [0.116]	0.381* [0.069]	0.378* [0.069]	0.663** [0.021]	0.601** [0.023]	0.601** [0.022]
Log GDP	-0.088 [0.445]	-0.158 [0.149]	-0.170 [0.113]	-0.052 [0.591]	-0.112 [0.224]	-0.127 [0.153]
Inflation	-0.041** [0.030]	-0.037 [0.106]	-0.035 [0.111]	-0.063** [0.042]	-0.051* [0.079]	-0.048* [0.078]
Depth of credit information				-0.163** [0.046]	-0.128* [0.081]	-0.130* [0.079]
Constant	-0.239 [0.858]	1.768 [0.180]	2.081 [0.119]	-2.215 [0.171]	-0.392 [0.786]	-0.073 [0.956]
Observations	311	311	311	311	311	311

Table 6.A.2. Asset-weighted results (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted R-squared	0.163	0.203	0.201	0.208	0.225	0.224
Countries	41	41	41	41	41	41

Notes: This table reports the results of estimating model (1) with weighted OLS. The dependent variable is the logarithm of Z-score.  $Z\text{-score} = (\text{ROA} + \text{CAR}) / \sigma(\text{ROA})$ , where ROA is the return on assets and CAR is the capital-asset ratio, which are both averaged over 2000-2008.  $\sigma(\text{ROA})$  is the standard deviation of return on assets over 2000-2008. A higher Z-score implies less risk. The weights are the bank's total assets. Heteroskedasticity-robust p-values, clustered by countries are reported in brackets. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table 6.A.3. Country results

	(1)	(2)	(3)	(4)	(5)	(6)
Contract enforcement days	0.076 [0.107]	0.075* [0.095]	0.076 [0.106]	0.091** [0.021]	0.089** [0.022]	0.089** [0.027]
Contract enforcement cost		-0.788 [0.183]	-0.775 [0.189]		-0.510 [0.313]	-0.505 [0.332]
Recovery rate			-0.116 [0.918]			-0.049 [0.963]
Information sharing	-0.061 [0.864]	-0.076 [0.821]	-0.077 [0.822]			
Creditor rights	0.104* [0.081]	0.063 [0.338]	0.067 [0.410]	0.098 [0.119]	0.072 [0.295]	0.074 [0.372]
Diversification index	-0.490** [0.036]	-0.464** [0.039]	-0.460** [0.038]	-0.532*** [0.006]	-0.510*** [0.008]	-0.508*** [0.008]
Overall capital stringency	0.001 [0.991]	-0.017 [0.851]	-0.016 [0.855]	0.006 [0.942]	-0.006 [0.943]	-0.006 [0.945]
Financial statement transparency	0.123 [0.465]	0.182 [0.320]	0.179 [0.319]	0.182 [0.188]	0.214 [0.143]	0.213 [0.141]

Table 6.A.3. Country results (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
MFI size	0.068 [0.557]	0.070 [0.552]	0.078 [0.550]	0.074 [0.498]	0.075 [0.494]	0.079 [0.538]
HHI	0.290 [0.464]	0.425 [0.318]	0.398 [0.432]	0.108 [0.779]	0.213 [0.608]	0.202 [0.693]
MFI growth	-3.282*** [0.000]	-3.302*** [0.000]	-3.257*** [0.000]	-3.747*** [0.000]	-3.717*** [0.000]	-3.697*** [0.000]
Log GDP per capita	0.060 [0.726]	0.031 [0.866]	0.039 [0.840]	0.314* [0.077]	0.274 [0.131]	0.278 [0.178]
Log GDP	-0.045 [0.665]	-0.103 [0.386]	-0.102 [0.389]	-0.048 [0.633]	-0.086 [0.443]	-0.086 [0.448]
Inflation	0.013 [0.688]	0.020 [0.518]	0.019 [0.544]	0.005 [0.839]	0.010 [0.676]	0.010 [0.696]
Depth of credit information				-0.156** [0.038]	-0.143** [0.047]	-0.143** [0.050]
Constant	1.817 [0.594]	3.489 [0.390]	3.298 [0.375]	0.099 [0.970]	1.317 [0.683]	1.238 [0.700]
Observations	40	40	40	40	40	40

Table 6.A.3. Country results (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted R-squared	0.276	0.278	0.25	0.361	0.348	0.322

Notes: This table reports the results of estimating model (1) at the country level. The dependent variable is the logarithm of Z-score.  $Z\text{-score} = (ROA + CAR) / \sigma(ROA)$ , where ROA is the return on assets and CAR is the capital-asset ratio, which are both averaged over 2000-2008.  $\sigma(ROA)$  is the standard deviation of return on assets over 2000-2008. A higher Z-score implies less risk. Heteroskedasticity-robust p-values, are reported in brackets. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## *Chapter 7*

# Conclusion

## 7.1 Summary

This thesis started with the narrative of the founding fathers of socially responsible investment and microfinance: Luther E. Tyson and Muhammad Yunus, respectively. First we considered socially responsible investment in developed countries. In chapter 2 we find that compared to other stocks socially responsible stocks have relatively high prices, as measured by their low book-to-market ratio. Because of overpricing, we would expect that socially responsible stocks have lower risk-adjusted returns. Yet, we find that the risk-adjusted returns of socially responsible and irresponsible stocks are not significantly different. The explanation we offer is that the asset pricing model used to calculate risk-adjusted returns includes a book-to-market factor (Fama & French, 1993), which captures at least part of the overpricing. So in asset pricing models inspired by Fama & French (1993) the trade-off between financial and social performance is at least partly captured by the book-to-market factor.

One lesson from chapter 2 for microfinance is that even in a developed country like the US, with a stock market in which prices reflect the available information, socially responsible investment has an effect on stock prices. Given that there is no public market for microfinance investment to timely reflect the adverse effects of an excess supply of funding, the impact of excess demand is likely to be much bigger in microfinance investment. Although this thesis provides no evidence on this, anecdotal evidence suggests that the consequences of the popularity of microfinance in some regions are severe (Chen et al., 2010). In some countries too much money is chasing too few MFIs, which is aggravated by development banks that

are crowding out commercial funding by supplying cheap loans that could have been provided by MIVs as well. In some countries, excessive funding has created an unhealthy focus on growth, which has led to overborrowing and credit delinquency crises in Nicaragua, Morocco, Bosnia and Herzegovina and Pakistan (Chen et al., 2010).

The commercialization of microfinance with a move to profit-driven institutions and the possibility of microfinance institutions to attract commercial investment has connected the fields of microfinance and socially responsible investment. Commercialization is one of the most debated issues in microfinance today. For some people, like Rhyne (2009), commercialization is the best hope to serve the millions that are still unbanked today. To other people, like Muhammad Yunus, it represents the moral demise of an ideal to reduce poverty. Some of Yunus' concerns are warranted, as commercial MFIs are less likely to serve the poorest borrowers. Yet, this also implies that there will always remain opportunities for nonprofit microfinance to serve the poorest of the poor.

Taking the commercialization of microfinance as starting point, we try to answer a number of questions in this thesis that are relevant for socially responsible investors in microfinance. First, why invest in microfinance in the first place? An often-mentioned argument in favor of microfinance investment is its low correlation with other international assets, which could make it an attractive diversification instrument. In chapter 3 we test whether this indeed the case: we test whether adding microfinance to a portfolio of international assets shifts the mean-variance frontier outward. Here we find that investors obtain a significantly more diversified portfolio when they invest in microfinance banks and MFIs from Latin America, which has the most commercialized microfinance sector. By contrast, nonprofit organizations like NGOs and microfinance institutions that operate in Africa, where operating costs are very high due to limited infrastructure, do not provide any diversification advantages. This is a striking result, because emerging market investments—to which microfinance investment are often compared—do not provide any diversification benefits (De Roon et al., 2001).

Given that a socially responsible investor decides to invest in microfinance, we ask to what extent investors face a trade-off between risk, return and outreach to the poor. Cull et al. (2009) and Hermes (2011) provide evidence that there is a trade-off between return and outreach. Chapter 4 provides suggestive evidence that there is also a trade-off between risk and outreach. Next, this chapter tries to quantify this trade-off by adapting the mean-variance framework of Markowitz (1958) to include

outreach. The findings in this chapter indicate that the price of increasing outreach is modest for a reasonable degree of outreach. Yet, to obtain very high outreach is quite costly in terms of foregone returns and extra risk.

Compared to studies that investigate the determinants of microfinance performance, risk—which is especially relevant to investors—has received less attention. In the introduction we mentioned that MFIs are susceptible to many types of risk. Chapter 5 and 6 focuses on two of these risks: governance risk and regulatory risk. Governance risk comes from the MFI itself and is due to suboptimal governance arrangements. In chapter 5 we investigate whether powerful CEOs are associated with more MFI risk taking. We show that especially powerful CEOs of NGOs increase an institution's performance variability. We do not find evidence that powerful CEOs are associated with better than expected performance; instead, they are associated with worse than expected performance. Therefore we conclude that good MFI governance guards against powerful CEOs.

In chapter 6, we investigate the effect of debt enforcement institutions on MFI risk. Typically, MFIs do not use debt enforcement institutions, because their loan sizes are too small and borrowers have no collateral. Surprisingly, we find that weak debt enforcement institutions reduce MFI risk. The explanation we offer is that microfinance has a competitive advantage vis-à-vis formal finance when debt enforcement institutions are weak, because it does not require collateral. The larger market for microfinance implies more diversification opportunities. Consistently, we find that weak contract enforcement is associated with less risk. Like Ahlin et al. (2010), we also find that weak contract enforcement leads to lower loan-size growth. So even though the pool of borrowers becomes bigger, weak debt enforcement limits MFIs' growth prospects.

## 7.2 Implications and limitations

Chapter 3 implies that there is scope for investors to use microfinance to better diversify their portfolio. Yet, for investors that are only interested in financial returns, only the more commercial MFIs are attractive. For investors also interested in the social returns, there are much more possibilities to invest in microfinance, because also the large number of non-governmental organizations and credit unions could be attractive investments. Still, chapter 4 shows that also these investors face a trade-off, because to invest in MFIs that serve the poorest they have to accept relatively large increases in risk and large drops in returns.

An important drawback of the methods used in chapter 3 and 4 is that they were not originally designed to be used on book data. MFIs are not actively traded and therefore have no market returns. Therefore, we had to rely on book data to conduct the spanning tests and form optimal portfolios. The book data from the MixMarket dataset could suffer from sample selection bias, as it mostly represents the better performing tier 1 and tier 2 MFIs.<sup>1</sup> Also the time span is relatively short and the number of MFIs used in forming optimal risk-return-outreach portfolios in chapter 4 is too small to be representative of the world's microfinance sector. Finally, the recent financial crisis has had effects on the real economy in developing countries. As a result funding has declined and repayment rates have deteriorated. Yet, the analyses in chapter 3 do not include the years of the financial crisis.

Both the financial crisis and microfinance repayment crises have put risk high on the agenda of researchers and policy makers. In the introduction we introduced many types of risk that are relevant to microfinance. Most of these risks have received little attention in the literature, but instead of a general analysis of all these risks, we focus on two specific risks. Like we discuss in chapter 5, especially in a sector like microfinance in which nonprofit institutions are often not regulated, good governance is of the essence. In addition, due to the dual objectives of microfinance there is much more leeway for directors to decide what they think is best. If this happens to harm the MFI financially, it is easy to argue that this decision improves social impact. Therefore, donors should be wary against directors that are too powerful and press for good governance with sufficient checks and balances.

Still, weak regulation in developing countries also offers opportunities for microfinance. We discuss in chapter 6 that with repayment rates as high as in microfinance and debt contracts that have no collateral, microfinance has much less need for an efficiently functioning court system. As long as proper institutions are not in place, microfinance could be a valuable first step in developing the financial sector in developing countries. Donors and social investors might therefore want to target their microfinance funding towards MFIs in countries with the least institutional development.

In any case, they should not target their funds to countries and regions where microfinance is already well developed, because overfunding could result in poor customers lending from multiple borrowers and ending up highly indebted. Des-

---

<sup>1</sup> Tier 1 includes mature, well-known, financially regulated MFIs. Tier 2 includes less well-known MFIs that are near profitability and candidates for conversion to for-profit status. Tier 3 includes mostly NGOs approaching profitability and tier 4 includes unprofitable start-up MFIs.

pite adverse effects of microfinance growing too fast in some regions, the popularity of microfinance among socially responsible investors has meant that millions of extra poor have access to financial services today. Without investors such growth would not have been possible. To some extent, firms in developed countries are concerned with socially responsible investment because the extra demand for their shares lowers their cost of capital. Given that in chapter 2 we find that the effect of socially responsible investment on prices and risk-adjusted returns in developed countries is fairly limited, microfinance investment looks like a more appealing instrument to push for social change.

Overall, microfinance appears to be attractive for investors, but there are several caveats. First, only the most profitable MFIs are attractive investments. Second, investors face a trade-off between financial returns and outreach to the poor. If they want MFIs to target poorer people, they have to give up financial returns. Third, MFIs are subject to many risks, on most of which there is little research. Although this thesis makes a start with investigating the determinants of microfinance risk, the impact of many other sources of risk still has to be identified.



# References

- Adams, R. B., Almeida, H., and Ferreira, D. 2005. Powerful CEOs and their impact on corporate performance. *Review of Financial Studies*, 18(4), 1403-1432.
- Ahlin, C., Lin, J., 2006. Luck or Skill? MFI Performance in Macroeconomic Context. BREAD Working Paper no. 132.
- Ahlin, C, Lin, J. and Maio. M. 2010. Where does microfinance flourish? Microfinance institution performance in macroeconomic context. *Journal of Development Economics*, forthcoming.
- Aiken, L.S. and West, S.G. 1991. Multiple regression: testing and interpreting interactions. Newbury Park, CA: Sage.
- Armendáriz, B., Morduch, J., 2005. *The Economics of Microfinance*. MIT Press, Cambridge, MA.
- Armendáriz, B. and Szafarz, A. 2009. On mission drift in microfinance institutions. CEB Working Paper, 9
- Bali, T.G., Demirtas, K.O., Levy, H., 2008. Nonlinear mean reversion in stock prices. *Journal of Banking and Finance* 32, 767-782.
- Banerjee, A.V. and Duflo, E. 2010. Giving credit where it is due. MIT working paper.
- Barth, J.R., Caprio, G., Levine, R. 2006. *Rethinking Bank Regulation: Till Angels Govern*. Cambridge University Press, New York.
- Barth, J., Lin, C., Lin, P. and Song, F. 2009. Corruption in bank lending to firms: cross country micro evidence on the beneficial role of competition and information sharing. *Journal of Financial Economics*, 91, 361-388.
- Bateman, M. 2010. *Why microfinance doesn't work*. Palgrave Macmillan, New York.
- Bauer, R., Koedijk, K., Otten, R., 2005. International evidence on ethical mutual fund performance and investment style. *Journal of Banking and Finance* 29,

1751-1767.

- Beck, T., Demirg-Kunt, A. and Peria, M. 2007. Reaching out: acces to and use of banking services across countries. *Journal of Financial Economics*, 85, 234-266.
- Beck, T., Demirg-Kunt, A., Laeven, L. and Levine, R. 2008. Finance, firm size and growth. *Journal of Money, Credit and Banking*, 40(7), 1379-1405.
- Bekaert, G., Urias, M.S., 1996. Diversification, Integration and Emerging Market Closed-End Funds. *Journal of Finance* 51 (3), 835-869.
- Biallkowski, J., Gottschalk, K., Wisniewski, T.P., 2008. Stock market volatility around national elections. *Journal of Banking and Finance*, 32(9), 1941-1953.
- Black, F., Jensen, M.C. and Scholes, M. 1972. The capital asset pricing model: some empirical tests in M. Jensen ed., *Studies in the Theory of Capital Markets*. New York: Praeger Publishers.
- Boyd, J., De Nicolò, G. and Loukoianova, E. 2009. Banking crises and crisis dating: theory and evidence. IMF working paper, no. 06/297
- Brown, M., Jappelli, T and Pagano, M. 2009. Information sharing and credit: firm-level evidence from transition countries. *Journal of Financial Intermediation*, 18, 151-172.
- Brown, M. B., and Forsythe, A. B. 1974. Robust test for the equality of variances. *Journal of the American Statistical Association*, 69, 364-367.
- Burgess, R. and Pande, R. 2005. Do rural banks matter? Evidence form the Indian social banking experiment. *American Economic Review*, 95(3), 780-795
- Byström, H.N.E. 2008. The microfinance collateralized debt obligation: a modern Robin Hood?, *World Development*, 36(8), 2109-2126.
- Cannella, B., Finkelstein, S., and Hambrick, D.C. 2009. *Strategic leadership: theory and research on executives, top management, teams, and boards*, Oxford: Oxford University Press.
- Cameron, A.C. and Trivedi, P.K. 2005. *Microeconometrics: methods and applications*, New York: Cambridge University Press.
- Campion, A., and Valenzuela, L. 2001. Credit bureaus. A necessity for microfinance? Microenterprise best practices project.
- Carhart, M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.
- Carroll, T.J., Niehaus, G., 1998. Pension plan funding and corporate debt ratings. *Journal of Risk and Insurance* 65, 427-443.
- Chen, G., Rasmussen, S. and Reille, X. 2010. Growth and vulnerabilities of microfin-

- 
- ance, CGAP focus note 61, Washington, DC: Consultative Group to Assist the Poor.
- Cheng, S. 2008. Board size and the variability of corporate performance. *Journal of Financial Economics*, 87(1), 157-176.
- Chua, C.T., Lai, S. and Wu, Y., 2008. Effective fair pricing of international mutual funds. *Journal of Banking and Finance*, 32(11), 2307-2324.
- Clare, A.D., Smith, P.N., Thomas, S.H., 1997. UK stock returns and robust tests of mean variance efficiency. *Journal of Banking and Finance* 21, 641-660.
- Cohen, L. 2009. Loyalty-based portfolio choice, *Review of Financial Studies*, 22(3), 1213-1245.
- Combs, J.G., Ketchen, D.J., Perryman, A.A. and Donahue, M.S. 2007. The moderating effect of CEO power on the board composition-firm performance relationship. *Journal of Management Studies*, 44(8), 1299-1323
- Consultative Group to assist the Poorest (CGAP) 2004. Key principles in microfinance. Washington: Consultative Group to Assist the Poor.
- Consultative Group to assist the Poorest (CGAP) 2007. CGAP Brief, Washington DC.
- Consultative Group to assist the Poorest (CGAP). 2008. Foreign capital investment in microfinance: balancing social and financial returns. Focus Note 44
- CSFI. 2008. Microfinance banana skins: risk in a booming industry, New York: Centre for the Study of Financial Innovation.
- CSFI 2009. Microfinance banana skins: confronting crisis and change, New York: Centre for the Study of Financial Innovation.
- Cull, R., Demirgüç-Kunt, A. and Morduch, J. 2007. Financial performance and outreach: a global analysis of leading microfinance banks, *Economic Journal*, 517: F107-F133
- Cull, R., Demirgüç-Kunt, A., and Morduch, J. 2009. Microfinance meets the market. *Journal of Economic Perspectives*, 23(1), 167-92
- Dam, L. 2008. Corporate Social Responsibility and Financial Markets. PhD thesis. University of Groningen: Groningen.
- Daily, C.M. and Johnson, J.L. 1997. Sources of CEO power and firm financial performance: a longitudinal assessment, *Journal of Management*, 23, 97-117.
- Demsetz, H. and Lehn, K. 1985. The structure of corporate ownership: causes and consequences, *Journal of Political Economy*, 93(5), 1155-1177.
- De Roon, F.A., Nijman, T. E., 2001. Testing for Mean-Variance Spanning: a Survey. *Journal of Empirical Finance* 8, 111-155.

- De Roon, F.A., Nijman, T.E., Werker, B.J.M., 2001. Testing for Mean-Variance Spanning with Short Sales Constraints and Transaction Costs: the Case of Emerging Markets. *Journal of Finance* 56 (2), 721-742.
- Derwall, J., Guenster, N., Bauer, R., Koedijk, K., 2005. The eco-efficiency premium puzzle. *Financial Analyst Journal* 61, 51-63.
- Deutsche Bank Research, 2007. Microfinance: An Emerging Investment Opportunity. Deutsche Bank, Frankfurt am Main.
- Dieckmann, R. 2007. Microfinance: an emerging investment opportunity, Deutsche Bank Research
- Djankov, S., La Porta, R., López-de-Silanes, F. and Shleifer, A. 2003. Courts. *Quarterly Journal of Economics*, 118, 452-517.
- Djankov, S., Hart, O., McLiesh, C and Shleifer, A. 2007. Private credit in 129 countries. *Journal of Financial Economics*, 84, 229-329.
- Djankov, S., Hart, O., McLiesh, C and Shleifer, A. 2008. Debt enforcement around the world. *Journal of Political Economy*, 116 (6), 1105-1149.
- Domini, A. 2001. Socially responsible investing: making a difference and making money, Dearborn Trade, Chicago.
- Driessen, J., Laeven, L., 2007. International portfolio diversification benefits: Cross-country evidence from a local perspective. *Journal of Banking and Finance* 31, 1693-1712.
- Eurosif. 2008. European SRI study 2008, European sustainable and responsible investment forum (Eurosif).
- Fama, E.F., MacBeth, J.D., 1973. Risk, return and equilibrium: empirical tests. *Journal of Political Economy* 81, 607-636.
- Fama, E.F., French, K.R., 1992. The cross-section of expected returns. *Journal of Finance* 47, 426-465.
- Fama, E.F. and French, K.R. 1993. Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics*, 33, 3-56.
- Fama, E.F. and French, K.R. 2007. Disagreement, tastes and asset prices, *Journal of Financial Economics*, 83, 667-689.
- Fama, E.F. and Jensen, M.C. 1983. The separation of ownership and control, *Journal of Law and Economics*, 26, 301-325.
- Feldstein, M., Seligman, S., 1981. Pension funding, share prices and national savings. *Journal of Finance* 36, 801-824.
- Ferson, W.E., Foerster, S.R., 1994. Finite sample properties of the generalized method of moments in tests of conditional asset pricing models. *Journal of Financial*

---

Economics 36. 29-55

- Finkelstein, S. 1992. Power in top management teams: dimensions, measurement, and validation, *Academy of Management Journal*, 35(3), 505-538.
- Finkelstein, S. and D'Aveni, R. 1994. CEO duality as a double-edged sword: how boards of directors balance entrenchment avoidance and unit of command, *Academy of Management Journal*, 37(5), 1079-1108.
- French, K.R. and Poterba, J.M. 1991. Investor diversification and international equity markets, *American Economic Review*, 81, 222-226.
- Friedman, M. 1970. The social responsibility of a business is to increase its profits, *The New York Times Magazine*, September 13.
- Gangopadhyay, S, Ghatak, M and Lensink, R. 2005. Joint liability lending and the peer selection effect. *The Economic Journal*, 115 (506), 1005-1015.
- Galbraith, J.R. 1973. *Designing complex organizations*, Reading, MA: Addison-Wesley.
- Galbraith, J.R. 1977. *Organization design*, Reading, MA, Addison-Wesley.
- Galema, R. 2010. Debt enforcement and microfinance risk, University of Groningen, working paper.
- Galema, R. and Lensink, R. 2011. Social investment in microfinance: the trade-off between risk, return and outreach to the poor, in B. Armendáriz and M. Labie (eds.), *Handbook of Microfinance*, World Scientific, NY.
- Galema, R., Lensink, R. and Mersland, R. 2010. Do powerful CEOs determine microfinance performance?, University of Groningen, working paper.
- Galema, R., Plantinga, A. and Scholtens, B. 2008. The stocks at stake: return and risk in socially responsible investment, *Journal of Banking and Finance*, 32, 2646-2654.
- Galema, R., Lensink, R. and Spierdijk, L. 2011. International diversification and microfinance, *Journal of International Money and Finance*, 30, 507-515.
- Ghatak, M. and Guinnane, T. 1999. The economics of lending with joint liability: theory and practice. *Journal of Development Economics*, 60 (October), 195-228.
- Giné, X. and Karlan, D. 2009. Group versus individual liability: long term evidence from Philippine microcredit lending groups, mimeo, Yale.
- Glaeser, E.L. 2003. Introduction to the governance of not-for-profit organizations, in E.L. Glaeser (ed.) *The governance of not-for-profit organizations*, Chicago: University of Chicago Press.
- Glaeser, E.L and Shleifer, A. 2001. Not-for-profit entrepreneurs. *Journal of Public*

Economics, 81, 99-115

- Glesjer, H. 1969. A new test for heteroskedasticity. *Journal of the American Statistical Association*, 64, 316-323
- Gonzalez, A., 2007. Resilience of Microfinance Institutions to National Macroeconomic Events: An Econometric Analysis of MFI Asset Quality. MIX Discussion Paper no. 1.
- Gouriéroux, C., Holly, A., Montfort, A., 1982. Likelihood Ratio Test, Wald test and Kuhn Tucker Test in Linear Models with Inequality Constraints on the Regression Parameters. *Econometrica* 50 (1), 63-80.
- Granger, C.W.J., 1998. Extracting information from mega panels and high frequency data. *Statistica Neerlandica* 52 (3), 258-272.
- GTZ. 2000. A risk management framework for microfinance institutions. Eschborn: GTZ.
- Hallock, K.F., 1998. Layoffs, top executive pay, and firm performance. *American Economic Review* 88, 711-723.
- Hambrick, D. C. and Finkelstein, S. 1987. Managerial discretion: a bridge between polar views on organizations, in L. L. Cummings & M. Staw (eds.) *Research in organizational behavior*, Vol. 9: 369-406. Greenwich, CT: JAI Press.
- Hannan, M. and Freeman, J. 1977. The population ecology of organizations, *American Journal of Sociology*, 82, 929-964.
- Hansen, L., 1982. Large sample properties of generalized method of moments estimators. *Econometrica* 50, 1029-1054.
- Hansmann, H.B. 1980. The role of nonprofit enterprise, *The Yale Law Journal*, 80(5), 835-901.
- Hartarska, V. 2005. Governance and performance of microfinance institutions in central and Eastern Europe and the newly independent states. *World Development*, 33(10), 1627-1643.
- Hartarska, V. and Mersland, R. Which governance mechanisms promote efficiency in reaching poor clients? Evidence from rated microfinance institutions, *European Financial Management*, forthcoming.
- Heinkel, R., Krause, A., Zechner, J., 2001. The effect of green investment on corporate behavior. *Journal of Financial and Quantitative Analysis* 36, 431-449.
- Helms, B. 2006. Access for all: building inclusive financial systems, Washington, DC: Consultative Group to Assist the Poor, World Bank.
- Hermes, N. and Lensink, R. 2007. The empirics of microfinance: what do we know? *Economic Journal*, 117(517), F1-F10.

- 
- Hermes, N., Lensink, R. and Meesters, A. 2011. Outreach and efficiency of microfinance institutions, *World Development*, forthcoming.
- Heal, G.M. 2005. Corporate social responsibility? An economic and financial framework. *Geneva Papers on Risk and Insurance: Issues and Practice*, 30, 387-409.
- Hillman, A.J., Keim, G.D., 2001. Shareholder value, stakeholder management, and social issues: what's the bottom line? *Strategic Management Journal* 22, 125-139.
- Hirsch, B.T., 1991. Union coverage and profitability among US firms. *Review of Economics and Statistics* 73, 69-77
- Holmstrom, B. and Milgrom, P. 1991. Multitask principal-agent analyses: incentive contracts, asset ownership, and job design. *Journal of Law, Economics, and Organization*, 7, 24-52.
- Hong, H.G. and Kacperczyk, M.T. 2009. The price of sin: the effects of social norms on markets, *Journal of Financial Economics*, 93(1), 15-36.
- Houston, J. and James, C. 1995. CEO compensation and bank risk: is compensation in banking structured to promote risk taking? *Journal of Monetary Economics*, 36, 405-431.
- Houston, J.F., Lin, C., Lin, P. and Ma, Y. 2010. Creditor rights, information sharing and bank risk taking. *Journal of Financial Economics*, 96 (3), 485-512.
- Huberman, G., Kandel, S., 1987. Mean-Variance Spanning. *The Journal of Finance* 42 (4), 873-888.
- Iyer, P.R., 2006. ICICI Joins Hands with Three VCs to Fund Microfinance Institutions. *The Economic Times*, June 5.
- Jappelli, T. and Pagano, M. 2002. Information sharing, lending and defaults: cross-country evidence. *Journal of Banking and Finance*, 26, 2017-2045.
- Janvry, A. de, McIntosh, C. and Sadoulet, E. 2010. The supply- and demand-side impacts of credit market information. *Journal of Development Economics*, 93, 173-188.
- Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48, 65-91.
- Jensen, M.C. and Meckling, W.H. 1976. Theory of the firm: managerial behavior, agency costs and ownership structure, *Journal of Financial Economics*, 3, 305-360.
- Karlan, D. and Zinman, J. (2009), Observing unobservables: identifying information asymmetries with a consumer credit field experiment, *Econometrica*, 77, 1993-2008. doi: 10.3982/ECTA5781

- Karlan, D. and Zinman, J. 2010a. Expanding credit access: using randomized supply decisions to estimate the impacts, *Review of Financial Studies* 23(1), 433-464.
- Karlan, D. and Zinman, J. 2010b. Expanding microenterprise credit access: using randomized supply decisions to estimate the impacts in Manila. *Innovations for Poverty Action* working paper.
- Karels, G.V. and Sackley, W.H., 1993. The Relationship Between Market and Accounting Betas for Commercial Banks. *Review of Financial Economics* 2 (2), 59-72.
- Kempf, A. and Osthoff, P., 2007. The effect of socially responsible investing on portfolio performance. *European Financial Management* 13, 908-922
- Khandker, S.R. 2005. Micro-finance and poverty: evidence using panel data from Bangladesh. *World Bank Economic Review* 19, 263-286.
- Kodde, D.A. and Palm, F.C., 1986. Wald Criteria for Jointly Testing Equality and Inequality Restrictions. *Econometrica* 54 (5), 1243-1248.
- Koenker, R. and Hallock, K.F. 2001. Quantile regression. *Journal of Economic Perspectives*, 15(4), 143-156
- Kogan, N. and Wallach, M. 1966. Modification of judgmental style through group interaction, *Journal of Personality and Social Psychology*, 4, 165-174
- Kramer, J.K., Vasconcellos, G.M., 1996. The economic effect of strikes on the shareholders on nonstruck competitors. *Industrial and Labor Relations Review* 49, 213-222.
- Krauss, N. and Walter, I. 2009. Can microfinance reduce portfolio volatility? *Economic Development and Cultural Change*, 58(1), 85-110.
- Kurtz, L., 1997. No effect or no net effect? Studies on socially responsible investing. *Journal of Investing* 6 (Winter), 37-49.
- Labie, M. 2001. Corporate governance in microfinance organizations: a long and winding road, *Management Decision*, 39, 296-301
- Laeven, L. and Levine, R. 2009. Bank governance, regulation and risk taking. *Journal of Financial Economics*, 93, 259-275.
- Lakshman, N., 2006. India's Banks are Big on Microfinance. *Business Week*, August 22.
- La Porta, R., López-de-Silanes, F., Shleifer, A. and Vishny, R. 1998. Law and finance. *Journal of Political Economy*, 106, 1113-1155.
- La Porta, R., López-de-Silanes, F., Shleifer, A. and Vishny, R. 1999. The quality of government. *Journal of Law Economics & Organization*, 15, 222-279.

- 
- Luoto, J., McIntosh, C. and Wydick, B. 2007. Credit information systems in less developed countries: a test with microfinance in Guatemala. *Economic Development and Cultural Change*, 55, 313-334.
- MacKinlay, A.C., Richardson, M.P., 1991. Using generalized method of moments to test mean-variance efficiency. *Journal of Finance* 46, 511-527.
- March, J.G. 1966. The tower of power, in D. Eston (ed.), *Varieties of political theory*, Englewood Cliffs, NJ: Prentice Hall.
- Markowitz, H. 1958. *Portfolio Selection: Efficient diversification of investment*. New Haven, Conn: Yale University Press
- Massie, J.L 1965. Management theory, in J.G. March (ed.), *Handbook of organizations*, Chicago: Rand-McNally.
- Mersland, R. 2009. The cost of ownership in microfinance organizations, *World Development*, 37(2), 469-478
- Mersland, R. and Strøm, R.Ø. 2009. Performance and governance in microfinance institutions, *Journal of Banking and Finance*, 33, 662-669
- Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42, 483-510.
- Microfinance Information Exchange, 2006. *Benchmarking African Microfinance 2005*. downloadable from [www.mixmarket.org](http://www.mixmarket.org).
- Microfinance Information Exchange, 2008. *Africa Microfinance Analysis and Benchmarking Report 2008*. downloadable from [www.mixmarket.org](http://www.mixmarket.org).
- Mischel, W. 1977. The interaction of person and situation, in D. Magnusson and N.S. Endler (eds.), *Personality at the cross-roads: current issues in interactional psychology*, Hillsdale, NJ: Prentice Hall.
- Mittelstaedt, H.F., Warshawsky, M.J., 1993. The impact of liabilities for retiree health benefits on share prices. *Journal of Risk and Insurance* 60, 13-35.
- Moerman, G.A., 2008. Diversification in Euro Area Stock Markets: Country versus Industry. *Journal of International Money and Finance* 27 (7), 1122-1134.
- Morduch, J. 1998. Does microfinance really help the poor? New evidence on flagship programs in Bangladesh. Draft, MacArthur Foundation project on inequality working paper, Princeton University.
- Moscovici, S. and Zavalloni, M. 1969. The group as polarizer of attitudes, *Journal of Personality and Social Psychology*, 12, 125-135
- Nelson, T. 2003. The persistence of founder influence: management, ownership, and performance effects at initial public offering, *Strategic Management Journal*, 24(8), 707-724.

- Newey, W., West, K., 1994. Automatic lag selection in covariance matrix estimation. *Review of Economic Studies* 64, 631-653.
- OECD. 2009. Corporate governance and the financial crisis: key findings and main messages, OECD Steering Group on Corporate Governance.
- Patten, R.H., Rosengard, J.K. and Johnston, D.E. Microfinance success amidst macroeconomic failure: the experience of Bank Rakyat Indonesia during the East Asian crisis, *World Development*, 29(6), 1057-1069.
- Persons, O.S., 1995. The effects of automobile strikes on the stock value of steel suppliers. *Industrial and Labor Relations Review* 49, 78-87.
- Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: comparing approaches, *Review of Financial Studies*, 22(1), 435-480.
- Pfeffer, J. 1997. *New directions for organization theory: problems and prospects*, Oxford University Press, New York.
- Pitt, M. and Khandker, S. 1998. The impact of group-based credit programs on poor households in Bangladesh: does the gender of participants matter?, *Journal of Political Economy*, 106(5):958-996
- Porteous, D., Collins, D., and Abrams, J. 2010. Policy framing note 3: prudential regulation in microfinance, Financial Access Initiative, NYU Wagner Graduate School.
- Reille, X., Glisovic-Mezieres, J., Berthouzoz, Y and Milverton, D. 2009. MIV performance and prospects: highlights from the CGAP 2009 benchmark survey, CGAP Brief, Washington, DC: Consultative Group to Assist the Poor
- Renneboog, L. Horst, J. ter, and Zhang, C. 2008. Socially responsible investments: institutional aspects, performance and investor behavior, *Journal of Banking and Finance*, 32, 1723-1742.
- Rhyne, E. 2009. *Microfinance for bankers and investors: understanding the opportunities and challenges of the market at the bottom of the pyramid*, McGraw-Hill, US.
- Roodman, D. and Morduch, J. 2009. The impact of microcredit on the poor in Bangladesh: revisiting the evidence. Center for global development working paper, Washington, DC.
- Rosenberg, Richard. 2007. CGAP reflections on the Compartamos initial public offering: a case study on microfinance interest rates and profits, CGAP focus note 42, Washington, DC: Consultative Group to Assist the Poor.
- Rosenberg, R., Gonzalez, A. and Narain, S. 2009. The new moneylenders: are the poor being exploited by high microcredit interest rates?, Consultative Group

- 
- to assist the Poorest (CGAP), occasional paper
- Sah, R.K. and Stiglitz, J. 1986. The architecture of economic system: hierarchies and polyarchies, *American Economic Review*, 76, 716-727
- Sah, R.K. and Stiglitz, J. 1991. The quality of managers in centralized versus decentralized Organizations. *Quarterly Journal of Economics*, 106, 289-29
- Salancik, G.R. and Meindl, J.R. 1984. Corporate attributions as strategic illusions of management control, *Administrative Science Quarterly*, 29, 238-254.
- Social Investment Forum (SIF). 2007. Report on socially responsible investing trends in the US.
- Steege, J. 1998. The rise and fall of Corposol: lessons learned from the challenges of managing growth, USAID Microfinance Best Practice, Washington, DC.
- Stephens, B., Tazi, H., 2006. Performance and Transparency: A Survey of Microfinance in South Asia. *The Microbanking Bulletin* 12, 22-34.
- Swanson, B., Undated. The Role of International Capital Markets in Microfinance, downloadable from [www.dwmarkets.com](http://www.dwmarkets.com).
- Tirole, J. 2001. Corporate governance, *Econometrica*, 69, 1-35.
- Thompson, S.B., 2011. Simple formulas for standard errors that cluster by both firm and time, *Journal of Financial Economics*, 99(1), 1-10.
- Yunus, Muhammad. 2007. Remarks by Muhammad Yunus, managing director, Grameen Bank. *Microcredit summit e-news*, July, 5(1).
- Wasserman, N., Nohria, N. and Anand, B. 2010. When does leadership matter? A contingent opportunities view of CEO leadership. in N. Nohria and R. Khurana, *Handbook of leadership theory and practice*, Boston: Harvard Business Publishing.
- World Bank. 2007. Finance for All? Policies and Pitfalls in Expanding Access. World Bank Policy Research Report, August, Washington, DC: World Bank.
- World Bank, 2008. Finance for All?: Policies and Pitfalls in Expanding Access, A World Bank Policy Research Report, The World Bank, Washington DC.



# Samenvatting

Microfinanciering is het verlenen van financiële diensten aan arme mensen, veelal in ontwikkelingslanden. Microfinanciering omvat alle vormen van financiële dienstverlening die we in ontwikkelde landen ook kennen, maar microfinanciering is vooral beroemd geworden door microkrediet: het verschaffen van kleine leningen aan arme mensen in ontwikkelingslanden. Na de hongersnood van 1974 bedenkt Muhammad Yunus na terugkomst in zijn thuisland Bangladesh dat arme huishoudens ook toegang zouden moeten hebben tot financiële dienstverlening. Hij begint daarom te experimenteren met het verstrekken van leningen aan arme dorpeelingen. Hierbij ontdekt hij dat armen baat hebben bij leningen en dat, ondanks een gebrek aan onderpand, arme mensen hem toch vaak terug betalen. In de daarop volgende jaren breidt Muhammad Yunus zijn experiment uit, wat resulteert in de oprichting van de eerste microfinancieringsinstelling, de Grameen bank, in 1983. Door het succes van de Grameen bank worden snel daarna overal ter wereld microfinancieringsinstellingen opgezet die vandaag de dag miljoenen armen helpen.

Voordat Muhammad Yunus het microfinancieringsexperiment opzette, waren het met name overheidsbanken die leningen verstrekten aan de armen, veelal boeren. Helaas was de bedrijfsvoering van overheidsbanken niet erg efficiënt. Ze hadden grote subsidies nodig en om politieke goodwill te bemachtigen vroegen ze te lage rentes en waren ze inconsequent in het innen van schulden. Begin jaren tachtig verleggen microfinancieringsinstellingen de focus naar de dienstverleningssector, die minder gevoelig is voor weerrisico's en prijsfluctuaties van gewassen. Daarnaast ontwikkelen ze speciale contracten voor het verstrekken van leningen aan cliënten zonder onderpand. Het meest beroemde contract is de groepslening waarbij groepsleden verantwoordelijk zijn voor elkaars lening. Door dit soort contracten krijgen microfinancieringsinstellingen soms wel 95% van het geleende bedrag terug.

Doordat arme klanten ook in staat blijken te zijn leningen terug te betalen, ondanks het feit dat ze geen onderpand hebben, realiseren beleidsmakers dat microfinancieringsinstellingen winstgevend kunnen opereren—ofwel: ‘Microfinancieringsinstellingen moeten financieel duurzaam opereren’. Dat betekent dat ze in de opstartende fase subsidies gebruiken, maar moeten streven om daar steeds minder afhankelijk van te worden. Uiteindelijk moet een instelling helemaal onafhankelijk zijn van subsidies en als een organisatie met winstoogmerk slechts afhankelijk zijn van private investeerders. Begin jaren negentig resulteert de hang naar financiële duurzaamheid erin dat instellingen zoals Bancosol in Bolivia voldoende waren opgeschaald om zich te transformeren naar instellingen met winstoogmerk.

Volgens voorstanders stelt de commercialisering van microfinanciering ons in staat om veel meer armen te helpen dan met non-profit microfinanciering alleen. Ongeveer 40 tot 80 procent van de populatie van ontwikkelingslanden heeft geen toegang tot financiële dienstverlening of wordt uitgebuit door woekeraars. Zonder commerciële investeringen, kunnen we nooit alle armen toegang geven tot de bancaire sector. Maar tegenstanders van de commercialisering vrezen dat instellingen met winstoogmerk de armen uitbuiten door te hoge rentepercentages te vragen, zodat de armen niet beter af zijn met microfinanciering dan met woekeraars. Ook vrezen ze dat het voor instellingen met winstoogmerk niet rendabel is om leningen te verstrekken aan de allerarmsten.

Cull et al. (2009) laten zien dat er ruimte is voor zowel commerciële microfinanciering als non-profitmicrofinanciering. Instellingen met een winstoogmerk hebben in totaal de grootste portefeuille, maar zonder subsidies slagen ze er niet in om de allerarmsten te helpen. Non-profitinstellingen daarentegen helpen in totaal het grootste aantal armen, met gemiddeld de kleinste leningen aan de armste mensen. Doordat non-profitinstellingen subsidie krijgen zijn ze beter in staat om de allerarmsten te helpen. Door commercialisering worden microfinancieringsinstellingen dus geconfronteerd met een afruil. Commercialisering stelt ze in staat meer kapitaal aan te trekken, sneller te groeien en zo meer armen te helpen. Maar het wegvallen van subsidies voor instellingen met een winstoogmerk betekent wel dat ze nu niet meer de allerarmsten kunnen helpen.

Gecommercialiseerde microfinancieringsinstellingen wenden zich tot de markt voor het aantrekken van kapitaal. Dit proefschrift draagt bij aan de discussie over commercialisering van microfinanciering vanuit het perspectief van investeerders. Waarom zijn investeerders geïnteresseerd in microfinanciering? Een eerste reden kan puur financieel zijn. Daarom onderzoeken we of microfinanciering diversi-

---

ficatie voordelen kan bieden en wat het risico van microfinancieringsinstellingen bepaalt. Een tweede reden om te investeren in microfinanciering is het sociale rendement. Ook voor (maatschappelijk verantwoorde) investeerders bestaat er een afruil tussen de financiële rendementen en de impact van hun investering op armoede bestrijding. Daarnaast wegen investeerders het risico mee van hun investering, zodat een maatschappelijk verantwoorde investering in microfinanciering wordt bepaald door de afruil tussen rendement, risico en armoedebestrijding. We onderzoeken hoe investeerders de optimale balans tussen deze drie doelen kunnen bepalen.

## Maatschappelijk verantwoord investeren

Investeren in microfinanciering is een maatschappelijk verantwoorde investering. Of investeerders moeten investeren in microfinanciering is gerelateerd aan de bredere vraag of investeerders maatschappelijk verantwoord moeten investeren. Het grootste deel van dit proefschrift heeft betrekking op investeren in microfinanciering, maar we onderzoeken ook maatschappelijk verantwoord investeren in algemene zin. Vandaag de dag realiseren veel publieke en private investeerders dat ze het gedrag van bedrijven kunnen veranderen door maatschappelijk verantwoord te investeren. Private investeerders investeren in maatschappelijk verantwoorde beleggingsfondsen en publieke investeerders zoals pensioenfonds ABP stellen maatschappelijke criteria op waaraan hun portefeuille moet voldoen.

Maatschappelijk verantwoord investeren is de laatste jaren enorm gegroeid. In de Verenigde Staten groeiden professioneel beheerde portefeuilles met 324% van \$639 miljard in 1995 tot \$2.700 miljard in 2007. Ter vergelijking, het totale universum van professioneel beheerde portefeuilles groeide met minder dan 260 procent van \$7.000 miljard tot \$25.100 miljard.

Maatschappelijk verantwoorde investeerders willen investeren op een manier die consistent is met hun waarden (Domini, 2001). Waar gewone investeerders willen dat aandeelhouderswaarde wordt gemaximaliseerd, willen zij dat de waarde van alle belanghebbenden (stakeholders) wordt gemaximaliseerd. Aandeelhouderswaarde en stakeholder waarde kunnen verschillen doordat activiteiten van bedrijven externaliteiten creëren. Vervuilende bedrijven maximaliseren mogelijk aandeelhouderswaarde door te vervuilen, maar niet stakeholders waarde wanneer ze de kosten van hun vervuiling niet internaliseren.

Er is een aantal manieren waarop investeerders maatschappelijk verantwoord

kunnen investeren. Een veelbeproefde maatschappelijk verantwoorde beleggingsstrategie is negatieve screening. Bij negatieve screening worden bepaalde bedrijven die niet aan de waarden van de investeerder voldoen uitgesloten van de portefeuille. Positieve screening, daarentegen, bestaat uit het kiezen van bedrijven die juist heel goed scoren op maatschappelijke verantwoordelijkheid. Vaak wordt positieve screening gecombineerd met een 'best-in-class' aanpak, waarbij alleen de meest maatschappelijk verantwoorde bedrijven worden geselecteerd. Naast het selecteren van de aandelen van maatschappelijk verantwoorde bedrijven, zijn er ook beleggingsfondsen die screening combineren met activistisch aandeelhouderschap waarbij wordt geprobeerd via de aandeelhoudersvergadering bedrijven te dwingen tot een meer verantwoord beleid.

Volgens Milton Friedman (1970), een beroemde tegenstander van maatschappelijk verantwoord investeren, is winstmaximalisatie de enige maatschappelijke verantwoordelijkheid van bedrijven. Iets anders maximaliseren zou ten koste gaan van de aandeelhouders. Daarnaast is het mogelijk dat maatschappelijk verantwoord beleggen extra vraag creëert naar maatschappelijk verantwoorde aandelen. Dat zou ervoor kunnen zorgen dat de prijzen van deze aandelen relatief hoger zijn dan die van aandelen zonder dit predicaat. In hoofdstuk 2 onderzoek we het effect van een maatschappelijk verantwoorde beleggingsstrategie op aandelenprijzen. In dit hoofdstuk vinden we dat een strategie van het kopen van aandelen die goed scoren op maatschappelijk verantwoordelijkheid de prijzen van die aandelen opdrijft. Het effect lijkt onderdeel te zijn van het book-to-market effect, aangezien we in een Fama-French prijsmodel (waarin voor book-to-market effecten wordt gecorrigeerd) geen positieve voor risico aangepaste rendementen vinden van een maatschappelijk verantwoorde beleggingsstrategie.

## **Investeren in microfinanciering**

Samen met andere maatschappelijk verantwoorde investeringen heeft investeren in microfinanciering de laatste jaren meer aandacht gekregen. In december 2008 investeerden buitenlandse investeerders al meer dan \$ 10 miljard in microfinanciering. Een van de meest gebruikelijke manieren om te investeren in microkrediet is door een zogenaamd 'microfinance investment vehicle (MIV)', wat een privé-entiteit is die fungeert als intermediair tussen microfinancieringsinstelling en investeerder. Hoewel er voorbeelden zijn van directe investering in microfinanciering, hebben investeerders vaak een voorkeur voor MIVs, omdat ze hun belangen

---

behartigen door 'due diligence' en toezicht en omdat ze het voordeel bieden van diversificatie over instellingen en landen. Momenteel zijn er zo'n 103 MIVs die wereldwijd ongeveer \$6,6 miljard onder beheer hebben.

Investeren in microkrediet is mogelijkwerwijs een goed alternatief voor andere investeringen in opkomende markten. Door de integratie van internationale kapitaalmarkten zijn investeringen in opkomende markten steeds sterker gecorreleerd met investeringen in ontwikkelde markten en bieden daardoor steeds minder mogelijkheden voor diversificatie. De cliënten van microfinancieringsinstellingen opereren in de informele markt, die wellicht minder gevoelig is voor macro-economische cycli. Kraus en Walter (2007) vinden dat microfinanciering inderdaad laag gecorreleerd is met internationale obligatie- en aandelenindexen.

In hoofdstuk 3 testen we met een 'spanning test' of microfinanciering de diversificatiemogelijkheden van investeerders vergroot. Hier vinden we dat het toevoegen van microfinanciering aan een portefeuille van internationale waardepapieren leidt tot een significante verbetering van de diversificatiemogelijkheden van investeerders. Dit is met name het geval wanneer het investeringen betreft in banken en MFIs uit Latijns Amerika, die de meest gecommmercialiseerde microfinancieringssector heeft. Nonprofits en instellingen die in Afrika opereren, waar de kosten hoog zijn door een gebrekkige infrastructuur, bieden geen diversificatievoordelen.

In hoofdstuk 4 kijken we hoe maatschappelijk verantwoorde investeerders in microfinanciering de afruil kunnen maken tussen rendement, risico en armoedebestrijding. In 1958 ontwikkelt Markowitz het 'mean-variance' raamwerk, waarbinnen het gemiddelde rendement afhangt van het risico (gemeten door variantie) wat investeerders lopen. Naast de afruil tussen rendement en risico voegen wij een extra overweging toe: armoedebestrijding. We meten armoedebestrijding als de gemiddelde grootte van een lening van een instelling; kleinere leningen impliceren armere klanten. Het maken van deze aanpassing in het raamwerk van Markowitz (1958) stelt ons in staat om de prijs van armoedebestrijding te bepalen. We vinden dat de prijs van extra armoedebestrijding (in termen van minder rendement en meer risico) relatief laag is voor een gemiddelde niveau van armoedebestrijding, maar relatief een stuk hoger wordt wanneer investeerders alleen instellingen in hun portefeuille willen hebben die de armsten van de armsten bereiken.

## Risico's van microfinanciering

Microfinancieringsinstellingen staan bloot aan vele risico's die hun langetermijn overlevingskansen beïnvloeden. In het laatste deel van het proefschrift proberen we te verklaren waarom sommige instellingen risicovoller zijn dan andere. In hoofdstuk 5 richten we ons op de risico's van bestuursstructuren (governance). In dit hoofdstuk onderzoeken we of MFIs met machtige leiders (CEOs) meer risico's nemen. We vinden hier dat vooral machtig CEOs van niet-gouvernementele organisaties (NGOs) variabiliteit van het rendement van organisaties verhogen. Deze variabiliteit lijkt vooral te komen doordat NGOs met machtige CEOs het slechter doen dan verwacht. Daarom concluderen we dat in een goede bestuursstructuur de CEO van een NGO niet teveel macht krijgt.

In hoofdstuk 6 verleggen we de focus naar externe risico's en kijken hoe de institutionele omgeving microfinancieringsrisico's beïnvloedt. Vooral in ontwikkelingslanden zijn de incasso-instituties erg zwak. In ontwikkelde landen duurt het meestal minder dan een jaar om insolventie op te lossen, waar het in ontwikkelingslanden vaak meer dan vijf jaar duurt om dit op te lossen. In hoofdstuk 6 postuleren we dat microfinancieringsorganisaties een competitief voordeel hebben ten opzichte van reguliere banken, wanneer instituties zwak zijn. Microfinancieringscontracten maken geen gebruik van onderpand, zodat het bekrachtigen van contracten via het rechtssysteem voor hen minder belangrijk is. Een grotere en diversere markt voor microfinanciering betekent meer diversificatiemogelijkheden voor de leenportefeuille van microfinancieringsorganisaties. In hoofdstuk 6 vinden we dan ook dat microfinancieringsrisico's lager zijn in landen met zwakke instituties voor incassoprocedures.