

Joint use of poverty scoring and credit scoring:
advantages and limitations of a new technique for socially oriented
and sustainability-minded microfinance institutions

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Abbreviations

ATM	Automated teller machine
DFI	Development Financial Institution
EUR	Euro currency
FICO	Fair Isaac and Company
GDP	Gross Domestic Product
GLP	Gross Loan Portfolio
GNI	Gross National Income
HR	Human Resources
ICT	Information and Communication Technology
KYC	Know Your Customer
MAD	Moroccan Dirham
MFI	Microfinance Institution
MIS	Management Information System
NBER	National Bureau of Economic Research, USA
NPO	Non-profit Organisation
PAR	Portfolio at Risk
PPP	Purchasing Power Parity
RoA	Return on Assets
RoE	Return on Equity
SME	Small and Medium-sized Enterprise
UN	United Nations
US, USA	United States of America
USD	United States Dollar

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Abstract

Financial institutions face adverse selection, in which risky borrowers are more likely to seek and take up loans. When interest rates increase, adverse selection rises, often disproportionately. Microfinance Institutions (MFIs), which generally operate with higher interest rates, are more exposed to adverse selection. Thorough credit analysis, collateral, credit reporting, and the imminence of legal or social pressure reduce adverse selection.

When interest rates drop due to subsidies or operational efficiencies, non-poor individuals seek microloans, particularly when banks deny or cap their credits. This demand for larger loans can tempt MFIs, especially when they are pressured to increase loan volumes while controlling costs. When MFIs seek to accommodate those who should not need microloans, they face a different form of adverse selection specific to microfinance. The significant presence of wealthier borrowers can damage an MFI's reputation. If such borrowers pose a greater-than-expected credit risk, because lenders might equate wealth with creditworthiness, wealthier borrowers can undermine the financial sustainability of the MFI.

Financial institutions, including MFIs, can use credit scoring to mitigate the first type of adverse selection. Credit scoring helps identify risky borrowers, allowing institutions to reject high-risk applications, price loans based on credit risk, and adjust the required guarantees.

To address the second type of adverse selection, MFIs can use poverty scoring. Similar to credit scoring, poverty scoring identifies loan applicants with a high probability of experiencing poverty. This technique allows MFIs to remain focused on their mission of serving the poor.

This thesis is the first to examine the joint use of credit scoring and poverty scoring in microfinance. It reveals the non-linear relationship between poverty and credit risk, showing that double bottom-line MFIs experiencing both types of adverse selection must use the joint technique to remain sustainable and focussed on financially excluded clients.

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As I was writing this thesis, the world witnessed a remarkable achievement: more than 200 million people globally escaped extreme poverty despite the unprecedented challenges and disruptions of recent years. I would like to extend my heartfelt thanks to the researchers, practitioners, and organisations whose work has directly or indirectly contributed to this significant progress. Their dedication to alleviating poverty and improving lives worldwide is inspiring, and their efforts deserve the highest recognition.

Chapter 1 Background of the study

This introductory chapter aims to position the thesis in the context of microfinance, which is both an industry in the financial services sector and a tool for combating global poverty. Credit scoring and poverty scoring are techniques that help microfinance institutions (MFIs) achieve financial and social objectives, respectively. This thesis analyses the joint use of these two scoring techniques by MFIs to avoid default and mission drift, which is a shift to accommodate wealthier borrowers. This chapter briefly defines what credit scoring is and what poverty scoring is in the microfinance context. It defines mission drift and presents the proposed solution to combat it with the joint use of credit scoring and poverty scoring. The chapter concludes with a presentation of the structure of this thesis.

1.1 Introduction

The first years of the third millennium witnessed the first space tourist. In 2001, Dennis Tito spent a week at his own expense on the International Space Station, orbiting the Earth 128 times. The year 2003 marked the completion of the sequencing of a human DNA. A year later, in 2004, two robotic rovers reached the surface of Mars to drive and explore the red planet, which has been venerated since Sumerian times. During the last days of 2004, Voyager 1 entered the heliosheath, a border region between the Solar System and interstellar space, becoming the first human-made object to approach the interstellar medium so closely, while being on the path to definitely leaving the heliosphere, an elongated bubble created by the solar wind that extends way beyond the orbits of the planets, protecting the Solar System from cosmic radiation.

While a myriad of instruments on Earth, Mars, and in remote parts of the Solar System explored the depths of the cosmos and the hidden realms of molecules and atoms in the early 2000s to help people understand the origins of the universe and humankind, the problem of poverty and precarious existence – so near, so obvious, and so urgent – lacked a robust solution, and still does today.

Technological progress has been, is, and should continue to be a wonderful phenomenon. Advances in science and technology must save the world from global warming and its predicted catastrophic consequences. More wealth can be created with the same inputs if know-how is

added to production. While the global output continues to grow at a faster rate than the world population, wealth distribution is determined by the use of the factors of production. Since technological progress makes it increasingly easier to substitute labour with other factors of production, the cost of unskilled labour decreases. For many working poor with low bargaining power, this is a serious challenge. Informal jobs for unskilled workers are underpaid. Formal jobs for unskilled people are either underpaid or, if better paid or offering social benefits, scarce. When systematically faced with underpaid jobs, the working poor from developing countries who have families to sustain have essentially two choices, both of which usually require an initial investment. They can either choose to create their own informal enterprises or emigrate to wealthier regions or countries to work and send money back home. It is not uncommon for one adult in the family, usually the husband, to work abroad and send money back home. Other adults in the family, usually the wife, with her or her husband's parents, along with the help of children, develop an enterprise at home.

If the husband or wife has a stable but low-paid job with important social benefits such as medical coverage for the family, subsidised housing, free schooling for children, or prospects of paid retirement, the other spouse will need to find a way to bring more money home. This can be achieved by either finding a better-paid job or developing an enterprise. The better-paid job option often requires the spouse to move to another place in the country or abroad. In societies where divorce is socially unacceptable, for dysfunctional marriages, the option of a better-paid job away from home brings additional, non-financial benefits. However, financially, this situation is not ideal for the family members at home, as the away spouse will send home less money than a similar person who is identical in all aspects but experiences a functional marriage.

For couples experiencing a functional marriage in which one spouse has a stable, low-paying job with long-term benefits, the 'at-home' entrepreneurial option for the other spouse offers additional benefits. Both spouses stay at home with other household members. Being one's own boss is, in itself, a reward for many, especially when compared with similar payoffs from informal or even formal jobs.

The entrepreneurial path one chooses out of necessity to make ends meet is hampered by several problems. Entrepreneurs attempt to combine the available factors of production in such

a way that the resulting added value significantly increases household income. In fact, the added value should exceed the sum of economic rents – the neoclassical definition of payments to the owners of factors of production in excess of the cost needed to bring them into production – that the household can collect by renting out available factors of production, including the labour of household members working for the enterprise.

The main problems experienced by out-of-need entrepreneurs, when there is no violence and socioeconomic shocks in the region, are access to finance, know-how, infrastructure, and support, different bureaucratic challenges, and psychological barriers (DeBerry-Spence and Elliot, 2012; Pratap *et al.*, 2017). In addition to the problems enumerated, women entrepreneurs struggle with gender discrimination and often with work-life balance (Abdulla and Ahmad, 2023).

Technological progress helps cut transaction costs, further facilitating access to finance (Ashta, 2011; Moro-Visconti, 2021). Advancements in information and communication technology (ICT), coupled with public and private investments in data infrastructure, facilitate the dissemination of know-how, reaching a vast majority of households, including the poorest and most remote, through cheap high-speed wired or mobile Internet. Technological progress enables virtual meetings, including conducting electronic Know Your Customer (e-KYC) procedures, so that poor entrepreneurs do not have to travel to the nearest branch of the financial institution, which might be dozens or hundreds of kilometres away in certain regions. Through digital signatures and payments, mobile wallets, and smartphones or tablets, technological progress helps entrepreneurs register their businesses, pay their taxes, receive scarce subsidies and similar governmental aid, and reach out to a much larger client base, often spreading beyond national frontiers (Saluja and Malik, 2024).

Social progress lags behind technological progress in many aspects related to the allocation of resources and sustainable distribution of wealth (Nowotny and Schot, 2018; Weeber, 2023). The consolidated efforts of nations have resulted in unprecedented gains in reducing extreme poverty globally over the last 40 years. If, at the beginning of the 1980s, more than 40 percent of the global population lived below the extreme poverty line – daily income below USD 1.9 at 2011 prices – in 2017, the share of the world population living below the extreme poverty line dropped below 10 percent for the first time in history (World Bank Group, 2024a). The

extreme poverty headcount ratio continued to decrease at a slower pace until 2020, when the Covid-19 pandemic struck. In 2019, the extreme poverty headcount ratio reached 8.5 percent (World Bank Group, 2024a). During the same period in which the extreme poverty headcount ratio dropped from above 40 to below 10 percent, the global population increased from 4.7 to 7.6 billion (World Bank Group, 2024a). This growth was mainly concentrated in countries with high rates of poverty.

In sharp contrast to the decline in extreme poverty, the poverty gap at USD 6.85 a day, at 2017 prices – the later introduced definition of a poverty line for upper-middle-income countries – did not decrease from 1981 to 2001, staying at or above 68 percent (World Bank Group, 2024a). To address the challenges faced by people experiencing poverty, especially those living above extreme poverty levels who could improve their circumstances through entrepreneurship and self-employment, the United Nations Economic and Social Council proclaimed 2005 as the International Year of Microcredit. In late 2004, the Secretary-General of the United Nations launched the International Year of Microcredit, stating that “Microfinance has proved its value, in many countries, as a weapon against poverty and hunger. It really can change peoples’ lives for the better, especially the lives of those who need it most.” (United Nations, 2004).

Following the 2005 Year of Microcredit, the Norwegian Nobel Committee granted the Nobel Peace Prize for 2006 to Muhammad Yunus and Grameen Bank for their effort to create economic and social development from below. The committee’s press release stated that “Lasting peace can not be achieved unless large population groups find ways in which to break out of poverty. Micro-credit is one such means. Development from below also serves to advance democracy and human rights.” (Nobel Media AB, 2006).

Microcredit allows poor people to borrow small amounts of money. Money is the most liquid form of capital – a factor of production – which can be converted through buying and renting to other forms of capital or to other factors of production, which are missing. Used as start-up capital, working capital, or as a source of funding for additional investments, microloans should leverage existing labour and other available factors of production to create additional added value. This extra added value should be shared among the providers of the factors of production. The borrower should be able to produce extra income to repay the microcredit and remain better off in the end. If this is the case, then the entrepreneur can create more wealth, in

relative terms, and part of it can be stored and accumulated over time. Under such assumptions, microcredit is a convenient aid tool because money lent carefully by a financial organisation is repaid and thus can be lent again to generate impact forever. The interest and associated fees which the institution collects from borrowers must cover the institution's operating costs, inflation, and the eventual depreciation of the currency. From this perspective of creating social impact, lending is in sharp contrast to the provision of subsidies and aid, which are often seen as one-time effect interventions.

Poverty is a multidimensional problem that includes social, economic, and political elements (Petrillo, 2018; D'Attoma and Matteucci, 2024). Solving the economic aspects of poverty from below seemed to be one of the world's poverty-related priorities at the brink of the millennium. Microfinance, with its main tool, microcredit, became the spearhead of this consolidated movement to help poor people leverage their entrepreneurial potential and the labour of household members to sustainably increase family income.

This thesis and the underlying research were inspired by this global movement to reduce poverty from the bottom up. The main research unit is the microfinance institution, which provides microcredit to financially excluded people, many of whom are entrepreneurs. The needs and particularities of financially excluded entrepreneurs are considered by these microfinance institutions when developing their loan products, as well as the required loan appraisal principles and procedures.

Microcredit closely resembles normal bank credit. Differences lie in the size of the loan and the trade-offs that microfinance institutions assume to cope with the relatively small ticket size of loans and assess the repayment capacity of potential borrowers. The microcredit is a formal loan with a small size relative to the national poverty line. Legally, it can be issued as a business loan, but it is often termed a personal loan meant for enterprise development. The microcredit should be reimbursed mainly from business revenues.

Because most applicants for a microcredit are financially excluded and thus cannot take an appropriate loan from a mainstream financial institution, non-usurious microfinance institutions have a double bottom-line. One bottom-line is financial – the conventional measure of the economic performance of the MFI expressed in profit amounts and profitability ratios.

The other bottom-line measures social performance – the positive impact the MFI creates in society, basically through the poverty alleviation effect of microcredit. When microloans have pollution reduction effects, microfinance institutions can claim a third bottom-line – the ecological one. Such microfinance institutions serve the ‘three Ps’ – people, planet, and profit, in the order they prefer. In all cases, microfinance institutions must remain financially sustainable if they want to be devoted to their main social mission which is to provide financial inclusion to people in need, most of whom are informal entrepreneurs.

This research investigates initially the separate and afterwards the joint use of credit scoring and poverty scoring by microfinance institutions. Before looking into the separate and joint use of credit scoring and poverty scoring, the research includes a literature review and a methodology section. The need for the joint use of credit scoring and poverty scoring is also assessed from the perspective of a double bottom-line MFI. Data volunteered by this MFI were used to determine whether poverty and the creditworthiness of its borrowers are strongly correlated. A strong correlation between poverty and credit riskiness – the opposite of creditworthiness – would render the joint use of poverty scoring and credit scoring useless, as poverty would be a strong predictor of loan repayment problems and default, and *vice versa*.

Credit scoring is a technique that helps credit institutions remain financially sustainable. Poverty scoring is a similar technique that considers the social sustainability of an institution. This thesis investigates whether the joint use of credit scoring and poverty scoring is a robust approach for microfinance institutions to simultaneously and methodically address their double bottom-line constraints.

This thesis appears to be the first research to investigate the joint use of credit scoring and poverty scoring by microfinance institutions. It aims to provide valuable insights for donors, microfinance investors, practitioners, and researchers about the particularities of the joint technique which involves the combined use of the two scoring techniques.

1.2 Poverty and economic inequality

Simply put, the main dimension of poverty is the scarcity of material possessions or money. Since money can be used to buy most goods and services or effectively rent various properties, poverty is a function of money.

Although we commonly refer to poverty in binary terms, such as a person being either poor or not poor, or a country being either poor in terms of its per capita gross domestic product (GDP) or not, poverty is, in reality, a continuous measure which decreases with wealth. The wealth itself is a dynamic variable. The stock of wealth increases with income and the receipt of transfers of wealth, such as inheritance. The stock of wealth decreases with expenses and outbound transfers, such as donations or the provision of dowries for daughters and sons when they marry and leave the household. Valuation can also alter wealth, even if income and expenditure flows remain constant. Commercial brand names and cryptocurrencies, different digital currencies that do not rely on any central authority to uphold or maintain them, are perfect examples of assets which depend purely on valuation.

To identify and fight poverty, the United Nations (UN) and other organisations agreed to measure people's income and, through this measure, derive their poverty level. It is assumed that those affected by poverty do not possess significant wealth. The income they receive serves mainly to cover the basic human needs of their family members. The monetary equivalent of fulfilling a fixed list of basic human needs of an average person is called a poverty line. Different public authorities can choose different combinations of basic goods and services deemed necessary for survival. Nevertheless, the UN operates with a global poverty line which is identical for all countries in terms of purchasing power.

Through these approximations, the poverty level of persons is inversely proportional to their income level. Once a person's income level crosses the set threshold, the person is not poor according to the logic set by the UN. If a person's daily or monthly income is above the respective threshold, this person is not poor in the view of those who consider that threshold. A person's income might exceed the threshold by a mere penny or by a large margin, but the result is the same – the person is not poor according to the poverty line in use. Those with an income slightly above the threshold might fall into the category of poor people if the threshold is increased. People who are slightly above the poverty threshold are not poor but are considered vulnerable, since a slight reduction in income or an increase in prices can drive them into poverty.

The UN poverty measurement technique represents a trade-off. It considers persons with significant wealth but small incomes as officially poor. Such persons can exploit the limitations

of the technique and qualify for certain welfare benefits if the providers of such benefits use the respective poverty measure. Another limitation is that people with high incomes but also high expenditures, who often experience severe limitations in meeting their basic human needs, are considered not poor.

It is assumed that the limitations of the UN poverty estimation technique, which is meant to identify severe poverty, are insignificant for measuring the extent of national and global extreme poverty. This study relied on the UN technique.

1.3 Microfinance

Microcredit is the provision of credit facilities to financially excluded individuals. Microfinance is a broader term which includes the provision of other financial services, such as savings, money transfers, and insurance, to people who cannot access or afford these services from mainstream financial institutions.

Poverty is the main cause of financial exclusion (Halkos and Aslanidis, 2023). Financial inclusion and the provision of microfinance services mean the same thing when the recipients of these financial services are households with low revenues.

Before the worldwide spread of modern-day microcredit, with some exceptions observed in certain religious communities, poor people were not provided credit services except by money lenders and loan sharks at high, often astronomical, interest rates ranging from 50 to over 1,000 percent per year (Wai, 1957). Microcredit enabled a reduction in these interest rates at the beginning of the 2000s to an average of about 28 percent per year (Rosenberg *et al.*, 2009).

The initial social innovation of microcredit was group lending. In the group lending approach popularised by Grameen Bank, the microfinance institution first lends money to two poor women in a group of five. If they repay, two more are given a loan, and if all four repay, the fifth also receives a loan (Yunus, 2003). The inside information of group members enables the group, and hence the MFI, to screen out bad borrowers but also avoid wealthier or much poorer borrowers, who could weaken the cohesion of the group of borrowers. Group members monitor, advise, and help each other in matters dealing with the loans. Members of different groups in the same village repay their micro loans to the MFI representative during public

sessions. Such events further reduce transaction costs, moral hazard, and future adverse selection. Portfolio at risk (PAR) and default rates are surprisingly low in many big MFIs practicing group lending. Based on such low risks and high returns, microcredit had been growing in the 2010s at 20 to 30 percent per year and was being offered to 205 million borrowers in poor countries, with most of these borrowers being among the poorest (Maes and Reed, 2012; Reed, 2012; Reed *et al.*, 2014). Simultaneously, learning from the experience of developing countries, microfinance initiatives started being encouraged in developed countries in a bid to financially include poorer segments of the population (Schreiner and Woller, 2003).

Group lending proved that poorer segments of the population in developing countries are creditworthy if the loan product is tailored to their needs and possibilities, and both adverse selection and moral hazard are reduced – appropriate screening mechanisms and repayment incentives are put in place.

Despite the rapid advent and success of group lending, individual microlending became the norm in developing countries, as it is in mainstream financing worldwide. Individual microlending is more costly than group lending, but it is also more flexible and better suited to the needs of microentrepreneurs. Many MFIs in developing countries have adopted individual microlending schemes in parallel with group lending. Other MFIs directly started offering individual microcredit products. It is worth noting that if the switch from group to individual lending was massive in microfinance institutions worldwide, the switch from individual to group lending happened only in extremely rare cases and was associated with significant improvement in the repayment behaviour of micro-borrowers (Carpena *et al.*, 2013).

In small, poor communities, members have access to the private information of other members. This information is generally inaccessible to institutions, just as information about non-declared revenues or informal employees in a business is hidden from MFIs and tax authorities. In group lending, operating in such communities, borrowers outsource several key tasks from the MFI, which are, business-wise, the responsibility of the financial institution. They efficiently screen bad borrowers. Group members make sure the repayment schedule is respected by struggling borrowers either by helping delinquent borrowers repay the instalment or by putting significant social pressure on them, so delinquent borrower finds somehow the money to pay the due instalment before all group members are punished. Group members

ensure the homogeneity of the group so that no tensions arise between the poorest and less poor members of the group. Access to private information allows the costs of the credit transaction to be relatively small, which translates into lower, more affordable interest rates, even if the borrowed amounts are small. Moreover, this mechanism which relies on access to private information and outsourcing of important business tasks to groups of borrowers, resolved the credit rationing problem – a market failure caused by information asymmetry and high transaction cost. Both information asymmetry and high transaction cost are accentuated by poverty. Both are causes of the financial exclusion of poorer entrepreneurs. Under credit rationing, credit is simply not extended to loan applicants, even if they accept paying a higher interest rate to compensate for the increased credit risk (Stiglitz and Weiss, 1981).

Donations from international organisations and charities, subsidies and technical assistance from projects centred on financial inclusion, and advances in ICT have reduced the cost of microcredit transactions in the case of individual lending, but the techniques of individual risk and wealth assessment have lagged behind. When microfinance markets started to saturate, competition among lenders, especially those providing individual microcredit, led to a set of issues related to bad loan repayment and deteriorating levels of credit portfolios. This may have led to aggressive actions on the part of lenders and social manifestations on the part of borrowers, some refusing to repay the loans as did the members of ‘No pago!’ movement in Nicaragua (Hrabalek and Zdrahal, 2013). Legislators have often clamped down on the sector, as in Andhra Pradesh, India (Mader, 2013).

Group lending certainly has its virtues in microfinance, but many micro-borrowers are better off taking individual loans tailored to their needs. One technique that MFIs could use for screening bad credit in individual lending on a large scale is credit scoring. The alternative is a costly loan appraisal procedure that often involves a visit by the loan officer to the business premises of the loan applicant. In addition to business visits, visiting the homes of entrepreneurs is also common practice in microlending. Repeat visits by a different loan officer or controller may be required in some institutions. These are generally concerned with the quality of the initial assessment of the microloan application conducted by the first loan officer, who, being often from the same community, might be biased and more prone to overestimating the profitability and repayment capacity of applicants, while overlooking eventual issues in the family or business of the same applicant. Approving a faster or larger loan to an acquaintance

would result in a bonus from the MFI for meeting loan production objectives, but also in a real or hypothetical bonus from the acquaintance for the loan officer.

Some biases of loan officers, such as those based on gender, age, or ethnicity, might result in fewer loans and suboptimal loan volumes, even if the loan officer misses all or part of the bonus for loan production.

MFIs can use poverty scoring to measure the probability of loan applicants experiencing poverty on a large scale and track their progress out of poverty. The alternative is a more costly analysis procedure which, if performed by junior employees, can raise concerns over quality and subjective judgement.

This research is focussed on the joint use of credit scoring and poverty scoring in microfinance institutions offering individual microcredit, mostly to microentrepreneurs. It is assumed that banks serve entrepreneurs who run larger businesses. Banks also serve formal employees. The reported salary of formal employees serves as the main indicator of their repayment capacity. Proof of salary and permanence of employment can be proven by a certificate from the employer and employment contracts or, ideally, by consulting the social security database or any equivalent registries that public authorities put in place to track the collection of relevant taxes and contributions to health and pension funds. Banks may use credit scoring to estimate the creditworthiness of potential borrowers. However, it will be mostly based on the official income, sociodemographic characteristics of the applicant, and the applicant's credit history. Some banks might have simple rules, such as offering the equivalent of three formal salaries in an overdraft facility for every employee who is formally employed for more than one year with the current employer. Many private employers underreport the actually paid salaries, to pay less taxes. Employees often do not object to such practices, as saved taxes can also benefit them. Underreporting the salary results in inferior repayment capacity, as calculated by the bank, and thus inferior credit limits. It would be very difficult for the employee to prove to the bank that the real salary is actually higher. Higher than officially earned incoming transfers could also be tracked by tax authorities as evidence of tax evasion.

People who work informally do not have proof of employment or formal evidence of recurrent revenue. Their salaries are paid in cash or kind and are not declared to tax authorities, thus,

these neither appear in official records, nor in company's official bookkeeping documents. Mainstream financial institutions generally avoid extending credit to this segment. In some countries, banks are prohibited from offering credit to people with no formal revenues for prudential reasons. These arguments often serve as indirect measures to discourage informal entrepreneurship and employment.

Microfinance institutions can offer credit to people who are informally employed, however, the repayment capacity of the potential borrower will be assessed mostly through applicant's wealth or through private information – when the loan officer or the branch manager knows the employer and trusts the employer with regards to providing private information about applicant's employment terms and perspectives of job security. As we argue in this study, wealth and creditworthiness might be weakly correlated in some segments of the population, often leading to bad credit decisions when wealth is considered a strong predictor of creditworthiness.

Microentrepreneurs usually invest borrowed money in productive activities, which should result in increased turnover and higher or more stable revenues and profits. Retail borrowers use borrowed money for consumer purposes, being tempted to buy goods or services now to pay for them later in instalments. Most instalment purchases involve a higher overall cost due to the applied interest rate and transaction fees. Some purchases of retail borrowers will result in improved skills when the borrower buys a course or training session, leading to possible higher salaries or better employment perspectives in the future. Some credit purchases will result in securing the current salary if the borrower uses the money to address a health issue or prevent health degradation. However, most retail purchases are not related to an increase in productivity or better employment security.

Retail borrowers, who are formally employed, have the legal and often moral right to purchase things on credit which will not increase their future productivity. Lenders would generally perceive such credits as low risk because the dissolution of a formal permanent working contract, at the initiative of the employer, usually involves termination benefits for the employee – money that can be used to repay the loan instalments and bills until a new job can be found. Even if a formally employed borrower is ill and temporarily unable to work, the employee will receive some social payments for the period of incapacitation.

Informal employees do not have the privilege of social protection and security. This vulnerability is one of the main reasons why informal employees are not the main category of borrowers of microfinance institutions. Certain microfinance institutions might exploit market opportunities offered by the massive presence of informal employees, but it is assumed that microentrepreneurs are the core clients of microcredit.

Even when microentrepreneurs are not the main clients of MFIs, the need for the joint use of credit scoring and poverty scoring in these MFIs, which is the main message of this study, remains important. The joint use of credit scoring and poverty scoring helps MFIs remain committed to obtaining social returns in addition to their own profits, if they choose to serve a double or triple bottom-line. Having a double or triple bottom-line implies impact investing, which means that funds are provided with the intention of social return in addition to the generally expected financial returns.

The supply chain of impact investing in microfinance usually ends when persons who are financially excluded obtain microcredits, which help them and their households increase revenues or, more rarely, avoid a deterioration in the current level of revenues. Because of market failure, market forces cannot provide the required supply of funds which target poor populations at market prices, especially when the microfinance industry in the country is in its early phases. The immediate upstream link in the supply chain of funds with an impact investing mission is the MFI. The MFI will struggle with its sustainability because of the same market forces, and it generally needs a supply of funds with an impact investing mission. The suppliers of such funds are usually developmental institutions, donor organisations, and social investment funds. Other organisations, including governments, non-governmental organisations, and religious societies, may participate in the supply chain. Generally, people or organisations which accept a lower financial return or a higher risk in exchange for certain social returns are at the origin of the supply chain of impact investing funds. By accepting financial returns below market rates, they expect to see proof of social returns. The MFI must do both: ensure that financially excluded people receive credit and that credit is repaid. The joint use of poverty scoring and credit scoring is one solution to this problem.

1.4 A simple definition of credit scoring and poverty scoring

We define credit scoring as a technique that employs algorithms developed using statistical methods to identify potentially bad credit transactions requested by prospective borrowers. Throughout the thesis, we use the term ‘bad credit risk’ to refer to bad credit transactions. Similarly, good credit transactions are referred to as ‘good credit risks’. A borrower whose loan is considered a bad credit risk is deemed to be a bad borrower. Credit institutions prefer to avoid bad credit risks and borrowers.

A credit score generally determines whether a loan application is accepted or rejected. The credit score could also determine if the loan application is sent for express approval, standard underwriting, careful underwriting, amendment of loan terms and requested guarantees, or direct rejection.

If credit scoring estimates the creditworthiness of the applicant, the poverty scoring technique employs algorithms developed using statistical methods to estimate the poverty status of the applicant. The main purpose of poverty scoring in financing is to determine the suitability of an applicant to receive financial services from the perspective of poverty. Such financial services are catered mainly to subjects with a certain poverty status, but subjects without it could use the services, diluting the impact these services produce in the targeted low-income subjects. This technique of poverty scoring uses approximately a dozen characteristics to help classify applicants as poor or not poor without measuring their income or wealth (Schreiner, 2010a).

If an organisation, private or governmental, needs to provide subsidised services or grants to poor people, it can use poverty scoring to decide who can access these services or grants. In economies with large informal sectors, a large share of the population would formally qualify as people with no or small incomes. In official records, most would appear as either unemployed or employed with small or minimally allowed salaries. Formal entrepreneurs would appear in official records as owners of enterprises which do not make a profit or simply do not break even. In reality, not all people with no or little formal income are poor. The provision of subsidised services or grants to all applicants with no or little formal income would result in faster depletion of budgets and fewer social outcomes. It can also result in frustrations and tensions in society due to the unfair but formally correct distribution of resources meant to

alleviate poverty. The use of poverty scoring would provide the organisation with a tool that helps empirically select poor applicants – or rather, screen out the non-poor ones. Although selection is not perfect, poverty scoring is probably the second-best option to identify poor subjects after the method of measuring real incomes, which is prohibitively expensive in most situations.

We define poverty scoring as a technique that employs algorithms developed using statistical methods to identify households with incomes above certain income thresholds. In microlending, the poverty score generally determines whether the loan application belongs to the targeted population, which is low income. Tracking the poverty score of a borrower over time can indicate changes in the household's income level. Many MFIs aim to help micro-borrowers increase their incomes and break the vicious cycle of poverty.

The joint use of poverty scoring and credit scoring by MFIs practising individual lending allows them to classify borrowers using two axes: poverty level and creditworthiness. If the poverty level is expressed with a poverty score – a positive continuous variable – or with a probability of poverty – also a positive continuous variable ranging from 0 to 1 – and if creditworthiness is expressed with a credit score or with a probability of repaying the loan on time, these two axes can form a matrix or a grid. If one of the axes is drawn horizontally and the other vertically, a matrix can be created and visualised. This matrix helps see what MFIs generally cannot: which borrowers are risky and poor, which borrowers are safe but still poor, which borrowers are risky and not poor, and which borrowers are neither risky nor poor. The matrix also shows the distribution of the portfolio across these four resulting categories of borrowers.

This novel method provides MFIs with new dimensions in screening risky applicants while addressing the desired segment of the population. It reduces the effects of information asymmetry that exists between MFIs and providers of impact investing funds, who may fear that the money they supply serves richer borrowers, leaving the poor outside the credit market.

1.5 The microfinance efficacy controversy and market forces

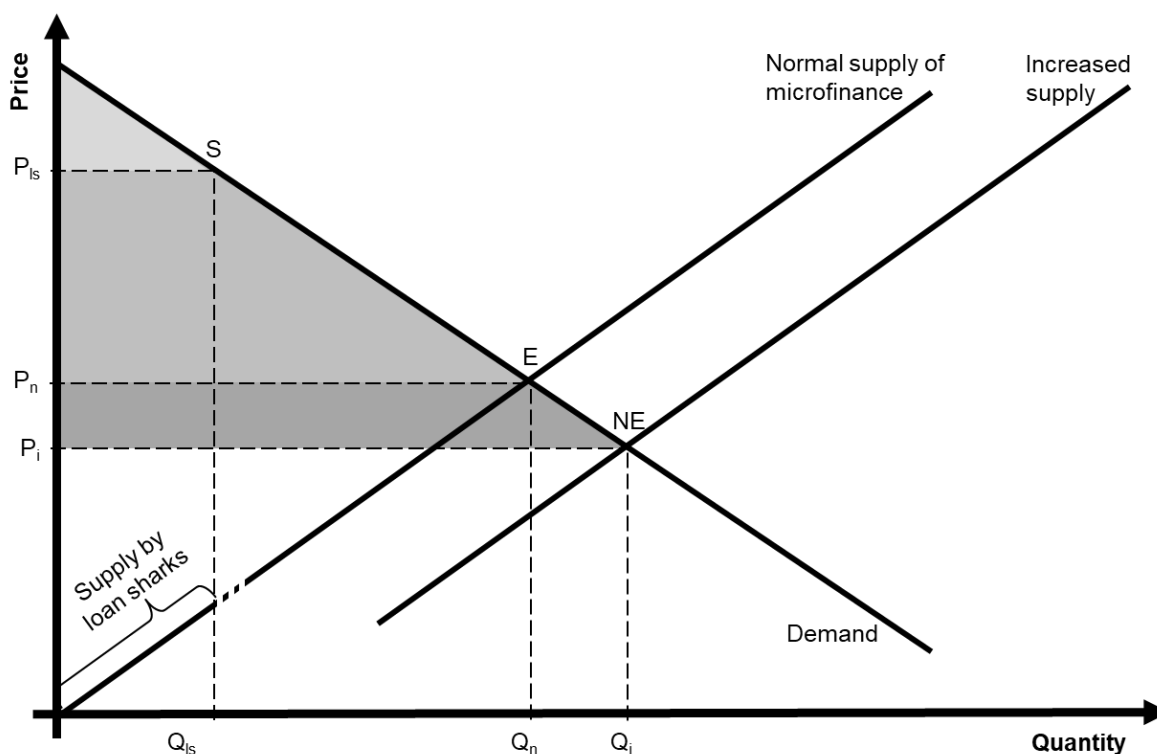
Since the late 2000s, there has been increasing controversy about the lack of efficacy or low efficiency of microfinance, mainly microcredit. The controversy unfolded, although there is

little doubt that the supply of services, where these are lacking, creates consumer surplus, while an increased supply further increases the consumer surplus. The ‘consumers’ of microfinance are predominantly microentrepreneurs who use the consumer surplus to develop or sustain their microbusinesses.

Figure 1 presents the supply and demand model commonly used in microeconomics to explain price determination in competitive markets. This model can also illustrate the loanable funds theory, which explains how the supply and demand for funds influence interest rates and the allocation of credit in an economy (Tsiang, 1987). While factors such as liquidity preference, imperfect information, emotional and cognitive biases, social norms, government interventions, and international capital flows are important considerations, they do not alter the fundamental principles of how the supply and demand for microloans work.

In Figure 1, following the downward-sloping demand curve for normal goods and services, including financing, we observe that at high interest rates – the price of financing – the market demand is limited to a relatively small quantity. This demand primarily comes from low-income individuals in urgent need of money who are willing to pay a high price. In the absence of specialised lenders, people borrow the amount Q_{ls} from loan sharks – informal lenders who charge extremely high interest rates and often use threats to collect missed payments. Despite these challenges, desperate borrowers still derive a certain positive utility, resulting in a consumer surplus – the small triangular area, shown in light grey, bounded by the price axis, the demand curve, and the line connecting point S on the demand curve and point P_{ls} on the price axis. The average interest rate these borrowers pay is P_{ls} – the highest indicated on the price axis.

Figure 1. Supply and demand model used to explain price determination and consumer surplus



Loan sharks may seek to increase the supply of financing at these high interest rates, potentially lowering the average price over time if borrowers repay consistently. However, they must operate discreetly to evade authorities and often other, more influential loan sharks in the market. To stay in business, loan sharks typically target the most vulnerable and desperate borrowers.

When MFIs enter the market, they alter the dynamics of price and quantity. Assuming they can reliably identify good potential borrowers, at least when the market is not saturated and MFIs can choose the best loan applicants, they increase the supply of financing, bringing the prices down. New market prices, such as P_n , attract significant demand. At such average interest rates, an increased volume of loans (Q_n) could be financed. The consumer surplus in this scenario is much higher – the area of the triangle, shown in darker (not the darkest) grey, delineated by the price axis, the demand curve, and the line linking point E on the demand curve and point P_n on the price axis. The light grey triangle covers the tip of the darker grey triangle.

The much higher consumer surplus should contribute more significantly to poverty alleviation among microentrepreneurs who apply for loans and have their applications approved. It is assumed that microentrepreneurs make informed decisions regarding borrowing costs and

benefits. Rational economic reasoning, rather than compulsive or irrational behaviour, typically guides their borrowing choices. This rational approach is crucial for the impact of microfinance because it ensures that loans are used effectively to foster sustainable business growth and income generation.

When organisations that support microfinance for its poverty reduction potential decide to provide grants or subsidised funding to MFIs or when authorities allow tax benefits which directly or indirectly result in a drop in the cost of microfinance, MFIs can provide more financing for micro-borrowers for the same price: a higher number of loan applications are financed, but also higher loan amounts are approved. The market experiences a shift in the supply of financing, which can be observed in Figure 1 under the ‘increased supply’ curve. Increased supply in a competitive market benefits demanders by lowering market prices and increasing traded quantities, that is, the volume of financing. If under increased supply the average price drops to P_i , the borrowed quantity will increase to Q_i . The consumer surplus in such case will be the area of the triangle, showed in darkest grey, delineated by the price axis, the demand curve, and the line linking point NE on the demand curve with point P_i on the price axis. This triangle represents the largest consumer surplus among the scenarios depicted in Figure 1 for competitive markets. The light grey triangle covers the tip of the darkest grey triangle too. The darker grey triangle covers most of the darkest grey triangle, however an area remains uncovered, indicating that the darkest grey triangle is the largest of all three triangles.

Keynes (1936) was probably the first to describe the inherent instability of the financial system, thereby contradicting the then-prevailing views that all competitive markets are self-regulating and tend towards equilibrium. He described how the psychological and behavioural aspects of borrowers and lenders impact market dynamics, emphasising the role of uncertainty. From this perspective, interest rates not only reflect the cost of borrowing money – as described in Figure 1 – but also help manage and price credit risk under uncertain conditions. The credit risk is priced using a risk premium. The risk premium compensates lenders for accepting the provision of funds under uncertain conditions. The premium is added to the general cost of funds, which reflects lenders’ demand for liquidity (Keynes, 1930).

More recent economic theory has identified the role of information asymmetry in shaping risk assessment, which, in turn, influences the credit market, challenging, like uncertainty, the

assumptions of perfect information (Akerlof, 1970). Information asymmetry in credit markets occurs when borrowers have more or better information than lenders regarding the risk involved in prospective credit transactions. In such cases, the agreed interest rate might include a risk premium that does not fully cover credit risk, jeopardising the lender's profits and sustainability. Information asymmetry can also occur when lenders abuse their position as the sole providers of financial services to certain borrowers by charging higher interest rates. In the latter case, concerned borrowers have less or worse information than the lenders.

The microfinance market, like most credit markets, is influenced by asymmetric information. In fact, it may be the most affected credit market. MFIs face challenges in assessing the creditworthiness of microloan applicants and their intended use of the borrowed funds. Many low-income households may be tempted to use loans or part of borrowed funds for consumption rather than business development purposes. These households can derive important utility from diverting borrowed funds for consumption. However, such behaviour would generally increase the credit risk of the loan, diminishing both the sustainability of the microenterprises and the sustainability of the MFI.

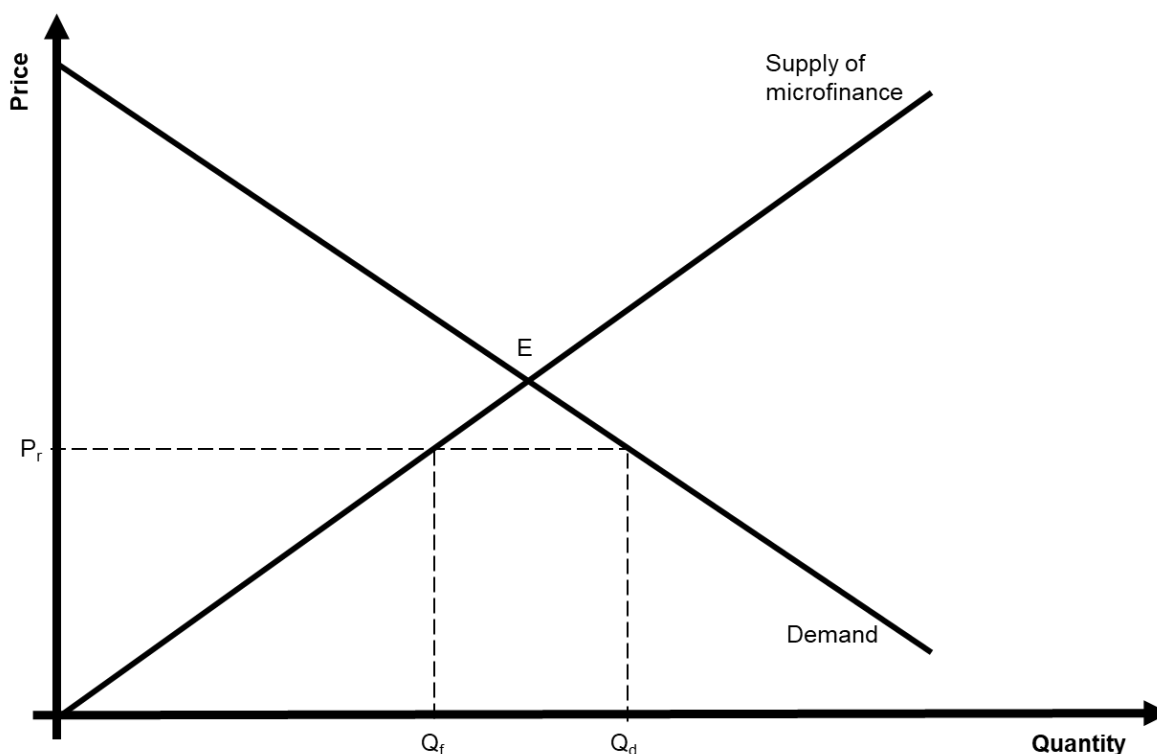
The informal environment in which microentrepreneurs operate exacerbates the problem of asymmetric information. Due to financial exclusion, which leads to limited experience with financing and often low literacy levels, loan applicants may overestimate the benefits of microloans, even when the borrowed funds are used strictly for income-generating activities. These aspects of information asymmetry – opacity and overconfidence – contribute significantly to adverse selection. Entrepreneurs seeking microloans, which are more expensive and more risky than traditional bank loans, may pose disproportionately higher risks. While microloan applicants may understand their higher risk profile, they may not fully disclose this to microfinance institutions, showcasing a classic case of information asymmetry. Moreover, microloan applicants may not be fully aware of the true costs of borrowing and may overestimate their ability to repay, thus increasing credit risk. Consequently, the actual credit risk is often higher than perceived, not due to deliberate withholding of information by one party but because loan applicants unknowingly provide biased information. Such cases may be more challenging for loan officers to detect than deliberate manipulation by applicants.

Information asymmetry appears to be the main cause of credit rationing in microlending. Credit rationing, an example of market failure, refers to a situation in which lenders limit the amount of credit issued to borrowers, even when there is demand from potential borrowers willing to pay higher interest rates (Stiglitz and Weiss, 1981). Figure 2 presents this situation using the microeconomic supply and demand model introduced above. Instead of the market finding its equilibrium at point E , where demand and supply meet, MFIs limit financing because they do not want to increase interest rates above a certain threshold. This increase could result in adverse selection when relatively good potential borrowers do not apply for expensive credit, while relatively riskier borrowers continue to apply, putting the quality of loan portfolios in danger when, due to information asymmetry, a disproportionate share of risky borrowers are judged as creditworthy and are financed. In Figure 2, the hypothetical price threshold that MFIs do not want to exceed is P_r . At such interest rates, micro-borrowers would demand to borrow a volume of loans Q_d , while MFIs are ready to finance a smaller volume Q_f .

It is worth noting that price caps imposed by legislators on microfinance lenders to limit usurious practices could function similarly to self-imposed limits by lenders due to information asymmetry. If P_r is the maximum interest rate that microfinance institutions are allowed to charge, the market will not reach equilibrium if the equilibrium price exceeds P_r . In such cases, legislators may inadvertently cause market failure, potentially creating more issues than the interest cap was intended to solve. If MFIs cannot charge interest rates above the cap, the volume of loans financed will be lower (Q_f), leaving a portion of potential loans ($Q_d - Q_f$) unmet, thereby causing financial exclusion. This exclusion might particularly affect those who need financing the most, especially if loan officers associate poverty with a higher credit risk.

Credit scoring plays an important role in the context of information asymmetry and adverse selection. If the credit scores reveal the true credit riskiness of loan applicants, all who are not very risky can be financed if they accept to pay the price. Even more risky loan applicants can be financed if they accept to pay an appropriate risk-adjusted interest rate – risk-based pricing.

Figure 2. Microeconomic implications of credit rationing on the demand for microloans



Segmenting loan applicants into homogeneous credit risk categories can help alleviate the credit rationing issue in microfinance. When MFIs accurately assess the credit risk of loan applicants, whether through credit scoring or other methods, they can determine, explain, and offer applicants appropriate interest rates for loans corresponding to each risk category. When applicants in these risk categories, not affected by adverse selection, understand and agree to borrow at the specified interest rates, each category should generate sufficient revenue to cover delinquency and default costs. Adverse selection might still play a role, as borderline clients – those who are at the very beginning of a riskier segment but who believe that they can still fit in the previous, less risky, and thus less costly risk segment – might refrain from borrowing at higher interest rates and seek to be included in one of the less risky segments. Their self-exclusion would slightly increase the average credit risk in the segment and thus would require an increase in the offered interest rate for that segment.

Offering an interest rate directly linked to the credit score, without segmenting loan applicants by credit risk, may also partially solve the credit rationing problem. Through risk-based pricing, MFIs can increase interest rates above the perceived threshold and finance more borrowers, further increasing consumer surplus.

Some may associate the risk-based pricing approach, when applied to risky micro-borrowers, with the venture capital model. However, unlike venture capital investments, where returns can increase exponentially in rare cases when financed businesses succeed see their valuation skyrocketing, lending revenues are confined to applied interest and fees. When a risky borrower successfully scales up the business and repays the loan, the MFI cannot claim a share of the profits generated during the repayment period. The MFI thus remains fully exposed to the downsides of the risky credit transaction, but upsides are limited to the applied and collected interest rates, be these much higher than for normal loans. As interest rates increase, they raise costs and reduce the borrower's profits, creating an inverse relationship with the borrower's likelihood of survival. Businesses operating with low profitability margins are often excluded based on straightforward loan feasibility calculations, whereas risky ventures with high margins may warrant further analysis.

Segmenting applicants by homogeneous credit risk categories or applying direct risk-based pricing based on credit scores has limits. MFIs may still hesitate to extend expensive credit for fear that insufficient applicants will fall into the high-risk and high-potential categories, making it challenging for these categories to break even.

When MFIs finance applicants whose risk turns out to be higher than expected, it often leads to increased instances of delinquency and defaults. To mitigate these risks, MFIs must intensify their collection efforts, thereby raising their operating costs. Financial losses from defaults and higher expenses for managing credit risk can undermine the financial sustainability of MFIs with deteriorating loan portfolios.

For micro-borrowers, defaulting on a loan disrupts the positive cycle of financial inclusion. Even for borrowers who do not default, if they overestimate the benefits of borrowing, the high costs of loans may offset any income gains, perpetuating or worsening their poverty.

Thus, the efficacy controversy is not rooted in market mechanisms, which increase financial inclusion when the supply of microfinance increases. The controversy centres on the long-term social impact of microcredit (Rosenberg *et al.*, 2009), particularly regarding the use of subsidies and grants to support an industry which may contribute to compulsive borrowing and over-indebtedness of poor populations. When MFIs seek to expand their loan portfolios, the

combination of pressure from loan officers and societal expectations to maintain a certain standard of living, coupled with low financial literacy and an overestimation of benefits, can lead to unnecessary borrowing. This cycle of borrowing beyond one's means and needs can exacerbate poverty, rather than alleviate it.

Credit scoring emerges as a vital tool to reduce information asymmetry. It enables MFIs to avoid financing high-risk loan applicants altogether or financing them at unsustainable costs. By informing both lenders and potential applicants about the likelihood of default, credit scoring has the potential to recalibrate MFIs' risk appetite and borrowers' overestimation of loan utility.

Similarly, poverty scoring can guide MFIs in targeting overlooked segments of the population that require financing. These segments may be poorer than those typically targeted by MFIs, but if they have the ability to repay loans, they can achieve financial inclusion and gain access to the lacking factors of production.

To produce and sell a good or service, one needs factors of production. These factors are classified into several groups, such as land, labour, and capital (Smith, 1776), and later, enterprise (Marshall, 1890). Early promoters of microcredit assumed that poor households need capital the most. It was expected that such households already have a microenterprise, which is an income-generating activity involving one or several members of the household and eventually one or several employees. The entrepreneur can provide the enterprise with the required labour by working implicitly for the enterprise, getting help from other family members, or hiring employees. It was assumed that such households have some land or real estate, if these are needed for production, or the entrepreneur can rent the required immovables. However, without capital, especially money – the most liquid form of capital – these poor households cannot sustainably develop their income-generating activities. Unable to develop these activities, these households do not accumulate wealth. Borrowing the needed capital at high prices would erode the profits of these microenterprises, preventing the household from accumulating wealth and breaking the status quo.

If we assume that borrowers correctly assess the utility of their microloans, two main causes hamper the social impact of microfinance. The first is the transaction cost. Microfinance

institutions, as middlemen, convey funds, whether commercially sourced or subsidised, from savings, investors, and donors to the end beneficiaries by charging a premium. This premium, which includes the credit risk component, acts against the effects of subsidies and increases the cost of funding. As a middleman, in exchange for the premium, the MFI performs the three functions of financial intermediaries: risk transformation, maturity transformation, and convenience denomination. The premium, which includes the costs and profit margin of the MFI, can be reduced without prejudice to profit if all transformation costs are reduced and credit risk can be estimated more accurately.

The second reason that hampers the impact of microfinance is consumption. When microcredit recipients do not invest in productive activities but buy consumer goods, there is a consumer surplus but no leverage effect. The consumer surplus is consumed. In many cases, spending credit money on consumer goods can have a positive effect on the ability of the household to be more productive. Home improvements can benefit residents, but the production of these residents can also increase due to better working and living conditions. Spending credit money on sanitation can increase the comfort of the household but can also decrease working members' sick time associated with poor sanitation.

An example of consumption with negative consequences on the household's ability to generate income could be when credit money is spent to buy an expensive TV set or a game console. Thus, productive time in the household is reduced because working members prefer to spend more time watching TV and movies or playing video games.

There are other causes which reduce the social impact of microfinance. These are related to entrepreneurship risks which are exacerbated by poor financial literacy, business informality, lack of safety nets, and lack of affordable business development services.

In an ideal setting, microcredit, when disbursed, would allow the borrower to invest in an income-generating activity which will generate added value above the cost of the microcredit and generate a cash flow surplus needed to repay the loan on time. When microcredit is reimbursed, the borrower is better off, and the money that facilitated the generation of the added value is back with the MFI and thus can be lent again to produce more economic and social effects. In this ideal setting, the interest rate and fees paid by the micro-borrower help the MFI

pay its bills and for its employees. Some of these employees would come from the same poor areas in which the MFI operates or seeks to expand. A portion of paid interest and fees would help the MFI reach new territories or other unserved segments of the population. A donor organisation which injects money into an MFI expects to see this money produce economic and social effects forever if the lending operations are sustainable and the money is protected from theft and inflation.

Any ideal microcredit setting is affected by adverse selection which will disturb the MFI's social mission, economic mission, or both. The concept of adverse selection, or antiselection, mentioned previously in the context of larger shares of risky borrowers applying for microloans when interest rates increase, was initially used in the insurance industry to describe people who bought insurance because they knew that they had higher risk factors than the average population and, in consequence, were more likely than expected to file insurance claims. In the microfinance context, adverse selection means the presence of loan applicants which are not generally targeted by the microfinance institution. When interest rates rise, adverse selection will represent the increasing share of riskier applicants who still want to apply for microcredit, while less risky applicants find it expensive and do not apply for microcredit. When interest rates fall, say due to subsidies or grants, adverse selection will represent the increasing share of non-poor applicants who find it appealing to apply for microcredit. The worst case is when the non-poor applicants are the riskiest. Wealth can signal better repayment capacity, but in reality, wealthier borrowers can abuse lax legislation or the weak capacity of the financial institution to enforce contract obligations.

An MFI concerned with double bottom-line objectives will find it difficult to navigate between the buoys imposed by sustainability needs and social objectives. Because the survival of the institution usually comes before its social goals, microfinance institutions strive to become sustainable in the first place. To achieve economies of scale, growth will be the main objective of the microfinance institution. The MFI will aim to continue growing after it breaks even. There are many incentives for an MFI to continue growing and increasing its revenue. Such motivations include the need to scale further to appear on the radars of investors and donors, offer competitive salaries to employees, attract talent, afford better offices and equipment, and increase the bonuses of top managers. One way to increase revenues and profits for a financial institution is to issue larger loans. Dealing with larger borrowers has benefits: the transaction

cost is generally lower as a proportion of the borrowed amount, larger borrowers appear more transparent, and they generally have better collateral. Returning to serving poorer borrowers becomes difficult if the MFI orients itself and adjusts to the needs of relatively larger borrowers.

The tendency of many microfinance institutions to expand into markets with wealthier potential clients is controversial. A systematic use of poverty scoring would have allowed users and their stakeholders to determine for individual MFIs, but also for individual countries, if the eventual growth in the average microloan is associated with a decrease in the share or in the number of poor borrowers, or, conversely, is associated with a growth in the share or in the number of poor borrowers. It is known that downscaling – in the microfinance context means tapping into segments of the population which can borrow relatively smaller loans – often implies a financial trade-off. Such trade-offs could be afforded if the MFI can increase revenue in other segments to finance the downscaling or get financial help from stakeholders.

It seems however that this financial help from stakeholders is a more prominent cause of the microfinance controversy, especially when it is coupled with reports of increasing over-indebtedness of poorer segments of population. Microfinance critics claim that the increased availability of money to be borrowed incites poorer, less financially literate people to binge on borrowing, mainly for consumer purposes, which increases their debt burden and expenses associated with the need to pay interest and associated fees, including late-payment fees which are generally an order of magnitude higher than the standard interest rates agreed with the lender. The use of subsidies to promote such behaviour among vulnerable populations, even if funds are repaid and lent over and over, would create a non-trivial controversy.

Here again, the use of poverty scoring would have allowed individual MFIs to measure the impact of their loan transactions. It could have been done at the cohort level – if the average poverty score of same borrowers decreases over time, then the general poverty level of this group decreases. Some individuals in the group can become poorer, including due to unthoughtful borrowings, but the group in general is better off. Under such conditions, a gradual increase in loan size is also justified, as the MFI has a moral obligation to support its clients' growth. The continuation of microfinance services to entrepreneurs who were poor when they started dealing with the MFI but who might not be poor today seems to be in line with the mission of microfinance, even if such borrowers might be considered financially

included because mainstream financial institutions would be interested in financing such enterprises.

Without a systematic, proper measure of poverty over time, discussions about controversial aspects of microfinance remain speculative. However, all such discussions need to recognise that, as mentioned earlier, the creation of a supply of services, where these are lacking, and further expansion of the existing supply, increase consumer surplus, which is the benefit borrowers get when they take microloans. This benefit, if microloans are taken in full awareness of the advantages and costs, should outweigh all expenses, leaving the micro-borrower better off at the end.

1.6 Understanding mission drift in micro lending

As has been argued, it is common to see microfinance institutions that practice individual lending progressively increase the size of loans they disburse. From a pure business approach, it is mainly about economies of scale, which are strongly desired in microlending to compensate for high transaction costs. Socially minded stakeholders fear an increase in the average loan. This could be the result of poorer clients being left aside, as they can only afford to borrow smaller loans, which represents a deviation from the original social mission of microfinance, also called mission drift.

Microfinance, by concept, is not just business. MFIs committed to serving the bottom of the pyramid can also increase the average loan to allow progressive lending. As micro-borrowers, who cannot otherwise formally prove or signal repayment capacity, show good credit behaviour with small loans, they generally receive larger credits. By showing the ability to reimburse a small loan without running into serious delinquencies, the information asymmetry between the borrower and lender is reduced. Convinced that the client is creditworthy, the lender is tempted to disburse a loan that better meets the needs of the borrower, that is, a larger loan.

MFIs may also see the average loan size increase as a result of cross-subsidisation, where relatively wealthier borrowers start receiving loans in larger amounts, and the profits MFIs generate in this way are used to cover the losses of core microlending.

Armendáriz and Szafarz (2011) define mission drift as an increase in the average loan size for purposes other than progressive lending and cross-subsidisation. They point to the difficulty in identifying mission drift which can be confounded with cross-subsidisation, a situation that can generate tensions between the MFI and its funders seeking social returns. Social investors seek to avoid investing in or supporting MFIs that abandon their social mission but solicit subsidised funding, justifying the increase in the average loan size by cross-subsidisation.

Progressive lending is generally easy to demonstrate. One can observe the first loan applications and amounts borrowed by clients who currently benefit from larger loans. If such borrowers were initially financially excluded, the loan application would show low revenues and little possession of productive assets. Low revenues determine the capacity to repay only relatively small loan instalments and thus small loan amounts. On rare occasions, the MFI can increase the loan term beyond 6, 12, or 18 months to issue a larger loan, but for applicants who apply for the first time with the MFI, this is an exception – the rule is to issue a short, small loan to observe how the new client behaves.

This thesis, which is a deeper and more rigorous continuation of the research presented in Bumacov (2012), addresses the core issue revealed by the research on mission drift: how can MFIs avoid it? In addition, how can one prove that the observed increases in the average loan size are not associated with a partial or total abandonment of the social mission of microfinance, which is to provide financial services and credit in particular to financially excluded segments of the population?

The proposed approach uses poverty scoring in combination with credit scoring to classify borrowers using two axes: poverty level and creditworthiness. This new technique, which is a combination of two similar scoring techniques, identifies which borrowers are risky and poor, which borrowers are safe but still poor, which borrowers are risky and not poor, and which borrowers are neither risky nor poor. It also shows the distribution of the portfolio across these categories – an imaginary X-ray picture – which shows the healthy portfolio, which has two parts: the socially desirable healthy portfolio and the healthy portfolio of relatively wealthier clients. The depicted unhealthy portfolio also has two parts: the unhealthy portfolio of poor borrowers – borrowers who need support – and the unhealthy portfolio of relatively wealthier borrowers – one which needs to be reduced and avoided in the future. A set of such X-ray

images made at regular intervals would allow to observe how the portfolio evolves over time with respect to credit risk and risk of mission drift. It is worth reminding that the distribution of the portfolio across the poverty level and creditworthiness axes is generally based on estimations. When the true class of the borrower is revealed such as when the loan goes into default (creditworthiness axis) and observed over time revenues prove that the borrower is not poor (poverty axis), the distribution of the portfolio across the two axes can be done using the real class of the borrower.

This new approach of using credit scoring and poverty scoring jointly can help measure and thus control cross-subsidisation and progressive lending in such a way that mission drift effects are reduced. This method gives MFIs new dimensions in screening applicants while focusing on the desired segments of the population. Social investors and funders dealing with funds which have a social mission should also find this technique interesting from the perspective of recommending it to MFIs or using it directly when conducting an independent assessment of the portfolio of concerned MFIs.

One might immediately object that if poverty is strongly negatively correlated with the capacity of individuals to repay loans, there will be no poor and creditworthy borrowers, just as there will be no wealthier and risky borrowers. There will be only poor and risky borrowers, less poor and less risky borrowers, and not poor and not risky borrowers. In such a case, the joint credit scoring–poverty scoring grid would be useless, and either axis – poverty level or creditworthiness – could be used to measure both the creditworthiness and poverty level of prospective micro-borrowers. Such an objection is generally exaggerated because research (Tabor and Bowers, 1977), although old, as well as microfinance practice, have shown that poorer segments of the population have varying levels of creditworthiness, justifying the need for developing credit scoring algorithms specifically for poorer borrowers. Moreover, this objection is not very relevant, even if the correlation between poverty and credit risk is high. MFIs with a social mission still need to provide credit to poor borrowers, even if a large proportion of these borrowers are not creditworthy. Observing and carefully managing cross-subsidisation will allow the MFI to remain sustainable, but the extent of financing non-poor borrowers must be controlled to ensure sustainability. Only the joint use of credit scoring and poverty scoring can help an MFI limit the extent of financing provided to non-poor borrowers,

selecting only those who are creditworthy, and cross-subsidising the financing of poor borrowers by focusing on the most creditworthy applicants.

1.6.1 There should be a mission first...

In microfinance, the social mission is implicit. The supply of microcredit, in particular, contributes to financial inclusion. As discussed extensively in the previous subchapter, if poor borrowers make rational choices when they borrow from formal financial institutions which aim to serve such segments of clients, the resulting financial inclusion contributes to poverty alleviation. The provision of subsidised funds and donations to MFIs increases the supply of microcredit, driving interest rates down and the number of borrowers up. Consequently, consumer surplus increases. The poor borrow more money at lower, more affordable interest rates. The interest, together with eventual loan appraisal, disbursal, and maintenance fees, that an MFI charges and collects from the borrowers, needs to cover funding and operational costs in the long run to ensure the survival of the MFI. Survival concerns all MFIs. Most MFIs, in addition to breaking even, aim to generate profit to be able to grow, pay the owners, increase the compensation of employees, or achieve other materialistic or philanthropic objectives. Profit represents the economic bottom-line, which is difficult to achieve, especially when subsidies are uncertain and scarce, transaction costs are high, and adverse selection-related expenses are difficult to control.

Due to the uncertain prospects of making a profit by lending to microentrepreneurs, mainstream financial institutions generally avoid this segment, even when it is relatively large. When regulators require these institutions, typically banks, to invest a certain percentage of their portfolios in micro-lending, they prefer to lend to MFIs or create their own MFIs rather than serve the segment directly.

For example, in 2021, the Central Bank of Egypt issued a directive requiring universal banks to achieve a 25 percent portfolio in SME clients by 2023, including 10 percent in small enterprises or microbusinesses. Most banks addressed this requirement by lending to MFIs, but some government-owned banks created their own MFIs or established microfinance departments within the bank. The profitability of such microfinance operations remains questionable. However, these banks can subsidise their microfinance departments to gain other advantages from the regulator or avoid penalties. Near the deadline, several large state-owned

Egyptian banks claimed to be among the first to achieve the Central Bank's objective, indicating both the difficulty of meeting this goal and the importance of signalling compliance to the authorities.

When banks deliberately enter and remain in direct microfinance operations, they financially include the subsegments they serve. These subsegments typically consist of larger microenterprises. As banks begin lending to these enterprises, the perceived boundary of microfinance shifts, excluding these enterprises from the traditional microfinance sector. Direct bank involvement redefines the microfinance segment, pushing out micro-borrowers who are then served by mainstream financial institutions. Consequently, microfinance institutions must seek smaller clients.

While MFIs might attempt to compete for microenterprises now served by banks, they often struggle to match the lower interest rates and comprehensive range of services that banks offer. However, MFIs can compete with banks by offering superior client relationships and higher-quality credit transactions, including faster and better tailored loans. MFIs can also potentially outcompete banks in terms of the quantity of lending to businesses, particularly those lacking full transparency. Unlike banks, which base loan amounts on formal profits and cash flows, often resulting in smaller loans, MFIs employ techniques to estimate a business's actual revenues, enabling them to offer significantly larger loans.

Cull *et al.* (2009) found evidence of trade-offs between the two missions of MFIs: serving the poor and achieving self-sustainability or certain profitability. In relative terms, smaller loans are more expensive to provide than larger loans. Moreover, higher interest rates, while potentially seen as unethical, can lead to adverse selection. Increasing interest rates may not be possible in many jurisdictions due to caps imposed by legislation. Finally, competition in the market may prevent the MFI from increasing interest rates to compensate for the high costs of small loans. Such situations put pressure on the social mission, and the MFI can slowly deviate from it in favour of the financial sustainability mission.

The research of Cull *et al.* (2009) also highlights the compatibility of the simultaneous pursuit of profit and social objectives. In the sample of Cull *et al.* (2009), self-sustainable MFIs tended to provide individual credits to relatively poorer clients. Contrary to expectations, larger and

older MFIs did not show profitability and deep outreach towards the very poor simultaneously. Consequently, mission drift and its associated problems remain central to microfinance.

1.6.2 What is credit scoring and what is poverty scoring? More elaborated definitions

Credit scoring is a technique that helps manage the loan granting problem: who is worthy of receiving a loan and who is not, based on the estimated probability of default. It requires the use of an algorithm that, using recent historical data, predicts the future behaviour of the loan applicant and classifies the applicant as a good or bad credit risk. The applicant necessarily belongs to a statistical population which is both homogeneous and massive, as is generally the case with micro-borrowers.

The credit scoring algorithm is derived using a multivariate analysis technique, such as regression or discriminant analysis, or, more recently, using artificial neural networks. Characteristics of the profile of the borrower which have credit risk discrimination power are identified. Weights will be attributed to these characteristics to compose the algorithm. The data used in the analysis represent the coded profiles of recent or current borrowers whose status as good or bad credit risks is already established. The assumption is that future borrowers will have credit behaviour resembling past borrowers with similar profiles.

Because prior to credit scoring implementation, past borrowers were screened by loan officers during their appraisal process, the population of clients with known credit risk status is subjectively biased as the MFI does not know how MFI-refused borrowers would have behaved if the MFI had disbursed them loans. As we suppose that a major part would have been bad credit risks – loan officers may be subjective, but generally manage to screen out bad applicants relatively well – the MFI must initially ensure that the algorithm also denies credit to the majority of applicants refused by loan officers.

The algorithm is developed using a sample of good and bad credit risks and is tested on a hold-out sample to avoid bias – it could be that the algorithm discriminates well between good and bad credit risks in the original sample, but when using the algorithm on a different sample or in production, it may not work. The algorithm-developing sample is also called the training or learning sample. The algorithm will learn, using the examples in the sample, that some

characteristics or combinations of characteristics are associated with bad credit risks, some with good credit risks, and some characteristics have no impact on the credit risk. The larger the sample size, the more robust the associations. The hold-out sample is also called the test sample because the credit risk discrimination power of the algorithm is tested on this sample. It is known that to describe an n -degree polynomial, one requires $n + 1$ data points. The hold-out or test sample ensures, in addition to the requirement to have large random samples, that the algorithm is not like the n -degree polynomial that perfectly fits the $n + 1$ provided data points but fails to fit additional data points.

In credit scoring, the credit risk discrimination power is what matters the most: how well the algorithm is able to identify bad credit risks and good credit risks, aiming at the lowest possible percentage of borrowers that are misclassified in what are called Type I and Type II errors. Type I error, also known as the incidence of a ‘false positive’, occurs when a good credit risk is classified as a bad credit risk – a bad credit transaction with a bad borrower, which is to be avoided. The credit scoring algorithm, which aims to identify bad credit risks, falsely identifies a good credit risk as ‘positive’ to the credit riskiness test. A Type II error, also known as the incidence of a ‘false negative’, occurs when a bad credit risk is classified as a good credit risk. Credit scoring identifies a bad credit risk as ‘negative’ to the credit riskiness test. These errors are reversed if we switch from a credit riskiness test to a creditworthiness test.

In an MFI that uses credit scoring with a scale where higher scores indicate a lower probability of default, and with a single cut-off score, all loan applications that fail to meet the cut-off are considered bad credit risks, while those that meet or exceed the cut-off are considered good credit risks. Passing the credit riskiness test means failing the creditworthiness test, and *vice versa*.

Type I error – the false bad credit risk – penalises the social mission of the MFI, while Type II error – the false good credit risk – penalises the profit-making mission by increasing the costs of the MFI related to bad credit risks.

The Type II error – the false good credit risk, which means that a true bad borrower is wrongly classified by the algorithm as a good borrower – is the most penalising error for the financial bottom-line of the MFI. However, depending on the context, this error can either support or

penalise the social mission of microfinance. This can partially support the social mission when the borrower takes a loan and, while failing to repay it, learns valuable entrepreneurial lessons on which she could rely when attempting to borrow again to develop a more sustainable small business. If the borrower defaults, but overall, the borrower is not worse off than before borrowing, it could be assumed that the funds that have been borrowed but have not been repaid produced some positive effects in the household of the borrower or in the microbusiness. From the lender's perspective, the default of a borrower is a bad thing. The unreimbursed money is lost. Expenses related to the collection of due money can further increase the loss for the MFI in the case of unsuccessful collection actions. Aggressive collection can deter other potential borrowers from engaging with the MFI, while lax collection actions can further increase moral hazard in current borrowers and adverse selection in potential borrowers by inciting risky entrepreneurs or fraudsters to apply for loans.

If the probability of default of a relatively risky subsegment of micro-borrowers is known, the MFI, in consultation with its stakeholders, can decide to serve the subsegment despite the risk, assuming a higher proportion of defaults in exchange for the opportunity to grow the businesses of subsegment representatives who do not default. The financial cost of the assumed defaults could be split between subsegment borrowers who did not default and repaid their loans and the corresponding fees, other safer borrowers, the MFI, and social investors, who are sacrificing a part of their financial returns in exchange for such social returns.

Type II error strongly penalises the social mission when, due to strong collection actions conducted by the MFI, the defaulted borrower loses important assets and gets a bad record in the credit history. Reports of suicide by defaulting micro-borrowers have shocked India (Ashta *et al.*, 2015), Sri Lanka (Colombo Telegraph, 2018), and other countries.

The sustainability of an MFI comes ahead of its social mission for objective reasons. The MFI needs to survive in order to take care of its social mission. Taking exclusive care of the social mission does not guarantee the survival of the MFI. For these reasons, the Type II error cost is significantly higher for the MFI than the Type I error cost. Microfinance institutions might operate with ratios of 1 to 4 or 1 to 5 – one bad to four good loans or one bad to five good loans – considering the financial gains a good borrower brings and the losses a bad borrower generates. It might take four or five good loans to compensate for the losses generated by one

bad credit risk. When social cost is added to the equation (four good loans divided by one bad loan), the denominator of the above fractions is generally reduced because when credit is given to borrowers who are classified as bad risks, financial inclusion reaches more people, including those who are creditworthy but have similar profiles to bad credit risks. Because credit scoring algorithms are far from perfect, there are score ranges, usually in the lower end of the score distribution, where the shares of good and bad credit risks are relatively high. The credit risk discrimination power of the algorithm in these score ranges is low. The MFI needs to make difficult choices, such as refusing all applications within a score range, approving most applications but facing high delinquency rates afterwards, conducting additional, more thorough analysis of applications, or letting applicants signal creditworthiness using mechanisms not yet considered by credit scoring. At the extremes of the credit score distribution, credit scoring algorithms usually manage to gather high shares of good credit risks – at the high end – and high shares of bad credit risks – at the opposite end.

The overall credit risk discrimination power of a credit scoring algorithm is measured and tested to determine whether it is statistically and economically significant. If acceptable, credit scoring is implemented and used in the process of screening loan applicants. The use of scoring is continuously monitored using credit scoring specific reports. As the repayment performance of newly granted loans will be revealed later – not all bad loans default in the first months – the MFI remains ‘blind’ for a certain period and has to rely on reports that measure how different the population of new borrowers is compared to the expected population.

Poverty scoring is a similar technique inspired by credit scoring. It employs algorithms developed using statistics mainly from poverty assessment surveys. Through numerous questions and observations, such surveys collect data describing the profile of the household, but also identify accurately the poverty level of each family. The same statistical techniques as in credit scoring are employed to identify the characteristics or combinations of characteristics associated with low-income households. Easily observable characteristics, such as the type of housing or availability of sanitation facilities, are preferable for greater reliability and fast assessment of the poverty level of the household. Mark Schreiner has done some remarkable work in developing and promoting the technique worldwide. His work includes a series of simple poverty scorecards for developing countries such as Bangladesh, Bolivia, Haiti, India, Mexico, Pakistan, and the Philippines, all grouped in (Schreiner, 2010b), some also being

published individually, such as (Schreiner, 2010a). Other developing countries have also been covered in the following years, while some old poverty scorecards have been updated based on new available data.

A notable difference between credit scoring and poverty scoring is that the latter estimates the current state of poverty instead of predicting the future credit behaviour of the potential borrower. The state of poverty is usually measured using the per head income. Due to the high volatility of earnings in low-income populations, measuring per head income accurately is difficult and costly. The added value of poverty scoring consists in a much faster and easier, yet accurate, estimation of the current state of poverty of a subject. By poverty scoring the profile of the household, the poverty level of household members is revealed. There is little interest in spending half of the day with the household trying to find out all earnings its members had last month or last year and filter declarative inconsistencies when there are easily observable indicators that suggest with high accuracy that the household is poor. Some of these indicators could be a separate kitchen in the house, car ownership, number of children, and the presence of a TV set in the house. These are country-specific characteristics, although similarities should be observed across many countries, especially neighbouring ones.

Another advantage of poverty scoring is the ability to measure the progress out of poverty of people who are scored at regular intervals. The beneficiaries of a poverty alleviation service, such as a micro loan, are poverty scored first before the provision of the service. After the service was fully provided – credit has been provided and repaid – they are scored again. A decrease in the average poverty score of the same clients will indicate that a certain proportion of the beneficiaries are no longer poor – a sign of a positive social impact due probably, in part, to the provision of the service.

1.6.3 Credit scoring and micro lending

Credit scoring has been used by financial institutions in the developed world since the 1960s (Weingartner, 1966), becoming a standard procedure in many countries, mainly in consumer credit. In microfinance, credit scoring is not new but is not in widespread use. Although the technique has proven its advantages over the pure judgmental approach to screen applicants (Viganò, 1993), few MFIs have incorporated credit scoring in their credit-granting procedures. The prediction that credit scoring would become the standard in microlending in the 2010s or

the 2020s has been overstated. The high cost of external consultancy, lack of know-how, and poor ICT and data infrastructure seem to prevent the widespread use of credit scoring in microfinance.

In contrast, poverty scoring is a newer adaptation of the credit scoring framework developed for targeting the poor and measuring their progression out of poverty. Notably, under the initiative of the Grameen Foundation (Innovations for Poverty Action, 2024), an increasing number of MFIs can afford to use the technique to assess the poverty level of their clients and measure their progress in overcoming poverty.

The use of credit scoring in microlending has certain specificities (Schreiner, 2000; Simbaqueba *et al.*, 2011). First, micro-borrowers usually operate in the informal or semi-formal sectors. Consequently, there are no reliable income statements or proof of turnover. The main quantitative measures, which indicate the viability of the income-generating activity, must be estimated, and the only way to do this is to send the loan officer to the premises of each and every applicant. The representative of the MFI will have to investigate, touch, and count the cash and assets to assess the daily turnover, from which weekly, monthly, and yearly turnover can be inferred. The procedure may be repeated randomly to obtain a better estimation. Borrowers, despite their relatively low financial literacy, learn quickly and know that showing a lot of cash, presumably from sales, is good for getting credit. Many would borrow money from relatives and neighbours on the loan application evaluation day in order to show it to the loan officer as proof of a high general sales volume.

Second, micro-borrowers generally do not have appropriate collateral. Assets are not reflected in bookkeeping documents, complicating credit risk assessment. Qualitative variables have an important weight in the evaluation of microcredit applications. It is not uncommon to see a credit disbursed mainly because other clients confirm that the applicant is a respected person in the community or to hear anecdotal stories of loan officers who do not disburse loans to stores that have dust on the shelves, which is proof of low turnover of displayed merchandise.

Third, since in microfinance the distinction between the moral person – the business (with legal status) – and the physical person – the owner with her family – is often blurred or simply nonexistent, the joint profile of the household and the microenterprise is analysed. The credit

scoring algorithm will include business-demographic variables, but also socio-demographic variables – combination which is not common in credit scoring for mainstream lending. Other types of variables describing the consolidated financial state of the applicant, including the household and the business, the characteristics of the requested loan, and the past credit behaviour are also used in developing the credit scoring algorithms.

Last but not least, in micro lending credit scoring generally cannot replace the loan officer as is often the case with consumer credit. The credit scoring tool is generally meant to help the loan officer take an informed decisions when approving or rejecting a loan application. In extreme cases – the credit score is either high or too low, the MFI can approve or reject a loan application without the opinion of the loan officer. The loan officer will however be responsible for collecting the information required for the calculation of the credit score. When the credit score is between the extremes, credit scoring helps the MFI, based on estimates of the probability of default, choose an approval strategy. If the credit score is relatively high and the requested amount is relatively small, a junior loan officer can approve the loan alone or together with the head of the branch. If the credit score is average, the MFI might delegate the credit decision to a more senior loan officer or to a credit committee. Credit scoring, in addition to solving the extreme cases, helps the MFI assign resources and competences based on the complexity of the prospective loan transaction. This complexity is determined by the probability of default of the future loan and the requested loan amount.

1.6.4 The synergy behind the new technique of using jointly credit scoring and poverty scoring

A tool that estimates both the creditworthiness and poverty level of a potential borrower can add high value to microfinance when deciding whether to grant a loan. Loan reimbursement depends on two factors: the ability and willingness to repay. Borrowers with higher incomes and net worth should have a better capability to withstand business shocks or personal problems, and still repay their loans. Wealthier borrowers do not necessarily have a stronger willingness to repay their loans than less wealthy borrowers. Some wealthy borrowers may become overindebted, as their assets can signal security to banks and MFIs, leading to competition among credit institutions to offer them larger loans without a thorough analysis.

It seems normal for a loan officer concerned about the quality of the portfolio under management to be tempted to disburse a loan to a relatively richer applicant, who may, in reality, be less creditworthy than a poorer person. It could be that the better-off borrower requested a micro loan because she was refused by mainstream lenders due to known bad credit behaviour records, unavailable to the MFI. Such credits that meet neither poverty level requirements nor credit risk requirements are likely to be approved simply because the client is wealthier and, consequently, judged more secure.

If the poverty level of potential micro-borrowers is weakly correlated or not correlated at all to their creditworthiness, MFIs should be able to categorise all borrowers using the matrix presented in Table 1. The matrix can have more or fewer rows and columns, depending on the needs of the institution, with a minimum of two columns to separate those below and above the selected poverty threshold and a minimum of two rows for bad and good credit risks.

Classification of people into poverty categories can be done using the United Nations' approach or following country- or region-specific poverty measures. Since poverty is a relative concept, MFIs may decide to conduct their own poverty assessment surveys and come up with their own definitions and limits specific to poor borrowers.

Table 1. A three-by-three poverty and credit risk matrix

		Poverty level		
		Poorest	Poor	Above poverty line
Credit risk	High	Poorest applicants with high credit risk	Poor applicants with high credit risk	Rich applicants with high credit risk
	Average	Poorest applicants with average credit risk	Poor applicants with average credit risk	Rich applicants with average credit risk
	Low	Poorest applicants with low credit risk	Poor applicants with low credit risk	Rich applicants with low credit risk

The poorest and poor applicants with low credit risk should be the primary target for an MFI aiming to meet its double bottom-line mission of serving the poor while covering all operational and administrative costs.

In contrast, if in microcredit the wealth of the borrower is a strong predictor of the future ability to repay loans, the matrix presented above will have only two groups: rich applicants with low credit risk and poor applicants with high credit risk, or three groups as presented in Table 2.

Table 2. Distribution of micro-borrowers, assuming a strong correlation between poverty level and creditworthiness

		Poverty level		
		Poorest	Poor	Above poverty line
Credit risk	High	Poorest applicants with high credit risk		
	Average		Poor applicants with average credit risk	
	Low			Rich applicants with low credit risk

In both cases, the matrix is an important tool to observe cross-subsidisation that could justify the need to provide loans to borrowers with relatively higher incomes and use the profits to sustain financing of low-income borrowers.

1.6.5 Observing cross-subsidisation

The matrix structure, such as the one presented in Table 1, reveals the existence of two types of subsidisation: intra-subsidisation and inter-subsidisation. ‘Intra’ refers to subsidisation inside the same poverty category. The topic of intra-subsidisation has not been covered by the microfinance literature from the perspective of mission drift analysis. It supposes that poor creditworthy borrowers pay in part for the losses generated by poor risky borrowers. Same applies for the better-off category: richer less risky borrowers pay in part for the losses generated by richer risky borrowers.

The MFI may apply a risk-based pricing strategy to reduce the effects of intra-subsidisation – riskier clients pay higher interest rates and by consequence, the extra revenues generated by the riskier borrowers that do manage to repay the loans cover the costs associated with higher levels of delinquency and default.

Intra-subsidisation inside the poor category of borrowers may be insufficient to cover the resulting operational deficit of the MFI. Increasing the interest rates applied to the low-income category of borrowers may result in strong adverse selection with additional losses that would exacerbate the sustainability issue of the MFI. If external support is not available or insufficient, inter-subsidisation is a potential solution for the sustainability issue generated by the financing operations involving low-income borrowers. ‘Inter’ refers to subsidisation across poverty categories and is the equivalent of the ‘cross-subsidisation’ term used by Armendáriz and Szafarz (2011).

In the case of inter-subsidisation, borrowers with relatively higher incomes, assuming they generate profit for the MFI through larger loans at almost similar transaction cost, compensate for the losses of low-income borrowers. But simply observing that an MFI has borrowers which are from the low-income clusters and borrowers which are from the relatively higher-income clusters is not yet proof of cross-subsidisation. These are also the symptoms of mission drift, when low-income borrowers are gradually replaced by relatively higher-income borrowers.

In order to be able to distinguish the mission drift, which is not desired in MFIs with a double bottom-line objective, from inter-subsidisation, which is often necessary to maintain the MFIs afloat, one needs to know the average costs and revenues by cluster in order to assess the extent of cross-subsidisation and deviation from the social mission.

1.6.6 Costs and revenues by cluster

Using basic cost control procedures, the MFI can estimate accurately the costs and revenues per loan in each cluster C_{ij} and calculate resulting earnings before taxes per each cluster – a gross profit P_{ij} . Since clusters are formed using a matrix, such as the one presented in Table 3, whose vertical axis represents the credit risk scale, which is divided in i segments, and the horizontal axis is defined by the poverty level of the borrowers, which is divided in j segments, each borrower can be assigned to a cluster C_{ij} based on the combination of the estimated credit risk and poverty level. Both credit risk and poverty level are estimated with credit scoring and poverty scoring respectively.

Table 3. Definition of ‘poverty – credit risk’ clusters and representation of gross profits in each cluster

		Poverty level		
		Poorest	Poor	Above poverty line
Credit risk	High	P_{11}	P_{21}	P_{31}
	Average	P_{12}	P_{22}	P_{32}
	Low	P_{13}	P_{23}	P_{33}

Knowing the number of loans in each cluster as well as the average unitary cost and revenue, the MFI or any other interested stakeholder may calculate the extent of intra-subsidisation, cross-subsidisation and mission drift.

To simplify calculations, the MFI may include in its costs the fair remuneration of the capital. The notion of ‘fair’ can be largely discussed, but having a targeted, say 5 percent return on

assets to further finance growth and make reserves for difficult times may be considered fair by all stakeholders.

In this case, the objective of the MFI will be zero gross profit. The gross profit in every cluster P_{ij} will be the difference between revenues and expenses in the cluster, including the remuneration of the involved capital.

If the sum of profits in the poor clusters $[\sum (P_{1j})]$ is negative, then lending to the poor segment is unsustainable and subsidies are necessary. An MFI that lends mainly to poor borrower will be entitled to seek donor funds or subsidised capital. On the other hand, if $\sum (P_{1j})$ is positive, then we conclude that lending to the poor segment is not only sustainable, but to a certain extent usurious – poor borrowers pay higher than necessary interest rates, as the targeted profit is zero.

Returning to the situation where lending to poor borrowers is unsustainable $[\sum (P_{1j}) < 0]$, if the sum of profits in the non-poor clusters $[\sum (P_{2j}) + \sum (P_{3j})]$ is positive then we observe cross-subsidisation. The profits made on wealthier clients are the source of subsidies that cover the losses made on the lending operations to poor clusters. On the other hand, if non-poor revenues exceed losses made on poor clusters, the excess can be attributed to the mission drift. More than that, the extent of the mission drift can be quantified in monetary equivalent or presented as a ratio – percentage of total assets.

Losses on financing clusters containing non-poor but risky borrowers $[(\sum (P_{21}) + \sum (P_{31})) < 0]$ represent a separate debate, as lending to such clients penalises the profit of the MFI and its social mission. Such losses, that can be named ‘inefficiencies’, will dissimulate the full extent of the mission drift if we compare only poor and non-poor borrowers. But if we define cross-subsidisation as compensation of losses made on poor borrowers $[\sum (P_{1j})]$ with profits made on non-poor less risky subjects $[(\sum (P_{22}) + \sum (P_{32}) + (\sum (P_{23}) + \sum (P_{33})))]$, then the deficit of non-poor risky borrowers is nothing else but a component of mission drift. This deficit should increase the value of drift’s metrics.

1.6.7 The use of the new technique based on the joint use of credit scoring and poverty scoring

The joint use of credit scoring and poverty scoring can produce new, relevant information, enabling ad hoc audits when MFIs that use both credit scoring and poverty scoring request subsidised financing or grants. These audits should be completed more quickly and with less effort, ensuring faster approval of requested funds, provided the MFI is both sustainable and committed to its social mission.

Implementing a tool based on the joint use of credit scoring and poverty scoring in an MFI makes sense in anticipation of future requests for social investment funds. The systematic use of such a tool to regularly manage the evolution of the portfolio across poverty–creditworthiness categories will ensure that the MFI fulfils both of its missions: financial sustainability and outreach to poorer segments of entrepreneurs. The results of these ad hoc audits will not surprise the MFI or its potential funders, even if the MFI is a for-profit organisation.

Counterintuitively, a commercial MFI might find greater benefits in using such a tool if it intends to attract subsidised capital. Since the MFI is able to channel received subsidised capital directly to the bottom of the pyramid and subsequently trace capital's social and financial returns, it can securely undertake the donor's mandate in seeking social returns. Considering the findings of Gonzalez and Rosenberg (2009), which state that commercial MFIs are more efficient than not-for-profit institutions, donors and socially oriented investors might shift their financing preferences to for-profit MFIs that use, or are willing to implement credit scoring and poverty scoring.

The novel tool based on the joint use of credit scoring and poverty scoring offers another advantage: it can help measure the progression of borrowers out of poverty. After repaying the first loan, a borrower will be reassessed using the same novel technique for credit renewal. In this case, the MFI may observe that the borrower is no longer in the 'poor' category but has 'migrated' to a less-poor cluster. Alternatively, the borrower may remain in the same poverty category but become less risky – still a favourable situation that typically grants access to cheaper credit.

As mentioned above, measuring social outcomes can be done by calculating the average poverty score of borrowers at the time the loan is provided and after it has been repaid. A reduction in the poverty score would indicate that the probability of the borrower being poor has decreased. When conducting such analysis at the cohort level, a drop in the average poverty score would clearly show that the group, on average, has become less poor.

1.6.8 Conclusions on usefulness of the joint use of poverty scoring and credit scoring

The joint use of poverty scoring and credit scoring techniques offers the advantage of grouping current and future borrowers into clusters based on their levels of poverty and credit risk. By calculating revenues and costs by cluster, the MFI can determine the levels of cross-subsidisation and mission drift at any given moment and track their evolution over time.

This new technique – and the corresponding new tool that should employ it – reduces the effects of information asymmetry between MFIs and their microloan applicants, as well as between MFIs and providers of subsidised capital. The latter may fear that the funds they provide will benefit wealthier borrowers, leaving poorer individuals excluded from the credit market. The novel matrix, resulting from crossing poverty scores with credit scores, helps address the double bottom-line equation that MFIs must constantly manage, which is arguably the most important equation in microfinance.

Using the same principles, we can imagine a cuboid – a three-dimensional tensor – that manages the triple bottom-line: the three ‘Ps’: Profit and Poor, common to all MFIs, plus Planet, specific to MFIs that additionally target ecological returns on investment.

Green finance is becoming increasingly popular as climate change intensifies, with developing countries facing heightened vulnerabilities. Extreme weather events disrupt daily activities and damage crop cultivation, which is crucial for food security and exports in many regions. Rising sea levels present additional challenges for coastal communities. Green finance supports investments in climate-resilient infrastructure and sustainable practices, helping these nations adapt to and mitigate environmental risks. It targets projects that balance economic growth with environmental protection, similar to how microfinance aims to balance economic growth with social outcomes and financial inclusion.

Currently, the largest development financial institutions (DFIs) provide green finance to local financial institutions in developing countries for on-lending to eligible investment projects. The eligibility of these green projects must be validated by the lender prior to financing, and often by the DFI after the investment is made. Such validation might require confirmation that the equipment or technology procured with the green funds comes from a list of pre-approved vendors, or, in the case of more sophisticated projects, a full assessment by specialised experts. However, these prior approvals are almost impossible to implement in microfinance institutions providing green finance due to their prohibitively high costs. ‘Green scoring’, developed based on the principles of poverty scoring, might allow green financing to be implemented effectively in microfinance.

In the section 8.5, dedicated to suggestions for future research, we discuss the feasibility and utility of green scoring in microfinance and small business lending.

1.7 The structure of the thesis

This thesis is composed of eight chapters. The current chapter concludes the introductory section and leads into Chapter 2, which is dedicated to the literature review. Chapter 3 presents the research methodology. Chapter 4 focuses exclusively on credit scoring, while Chapter 5 focuses on poverty scoring. Chapter 6 addresses the joint use of credit scoring and poverty scoring in microfinance, analysing quantitative data from various MFIs worldwide. In this chapter, the MFI is the subject of analysis. Chapter 7 continues the examination of credit and poverty scoring in microfinance, this time at the client level. A sample of microloans from an MFI is analysed with the aim of validating the theoretical constructs developed in the previous chapters and addressing the questions raised in Chapter 6.

Chapter 8 concludes the thesis. The concluding chapter not only presents all the findings of this research in a structured manner but also outlines the contribution of this thesis to economic and finance theory and microfinance practice. A separate section in the concluding chapter is dedicated to potential avenues for further research.

Chapter 2 Literature review

The literature on credit scoring in microfinance remains scarce. The literature on the use of poverty scoring in microfinance is even scarcer. To date, there is no literature covering the joint use of credit scoring and poverty scoring in microfinance, except for Bumacov (2012), a paper which lies at the origins of this research and concludes that the joint use of poverty scoring and credit scoring gives MFIs the advantage of grouping borrowers in clusters of a matrix based on their levels of poverty and credit risk. The matrix helps MFIs solve the double bottom-line equation ‘profit – people’. MFIs need to remain sustainable – make a profit, while avoiding drifting away from its social mission – providing financial inclusion to poor people.

2.1 Introduction

Credit scoring is a technique dating back to the 1940s. Since then, the use of credit scoring in mainstream banking became universal and the literature covering the topic of credit scoring is very ample. The history of credit scoring in developed countries, mainly USA, reflects the issues with which the financial institutions were confronted in providing credit. Some of the issues are similar to the ones faced by MFIs nowadays. Although several books present a history of credit scoring (Thomas, 2002; Anderson, 2007), none focused on the timeline of the use of credit scoring in microfinance or small business lending.

This literature review, which initially focusses on credit scoring, divides the evolution of the technique into different historical periods, each presented in a different subchapter based on the kind of subjects being studied predominantly in each period. We have characterised the time periods as: ‘Early works’, ‘The commercial era of credit scoring for consumer credit’, ‘Credit scoring for corporate lending’, ‘Institutionalisation’, ‘New dimensions of credit scoring’ and finally ‘The microfinance era’, with the latter looking more like a historic recurrence rather than a new historical stage.

In ‘Early works’ we trace the origins of credit scoring methodology, highlighting the contribution of David Durand. In ‘The commercial era of credit scoring’ we observe the improvement of the technique and its consequent adoption by consumer lenders. In the next period we describe the efforts to adapt the credit scoring technique to the needs of corporate lending, noting particularly the significant contribution of Edward I. Altman.

‘Institutionalisation’ saw the widespread use of the credit scoring technique and increasing interest from the US regulatory bodies. The emergence of a ‘New dimensions’ phase witnesses the increasing importance of software and ICT infrastructure. Finally, ‘The microfinance era’ presents the modest adoption of the technique by microfinance lenders.

After highlighting the milestones in the development of the technique of credit scoring, we present in the ‘Framework’ section the consolidated conceptual framework of the credit scoring technique, which we developed on the basis of this critical review of literature. The framework can be applied to personal, retail, mortgage, micro, small, medium, corporate, and other homogeneous loan markets. We use this framework to conceptually define poverty scoring too.

2.2 Early works

The set of studies in consumer instalment financing conducted by the US National Bureau of Economic Research (NBER) in the last years of the 1930s and published in 1940 and 1941 represents the base on which credit scoring emerged. The NBER, a non-profit organisation (NPO), was engaged at that time in researching and disseminating knowledge about essential economic facts. Instalment financing was one important economic activity in the USA. Loans outstanding doubled in the country from 1934 to 1938 (Chapman *et al.*, 1940).

Personal loans contributed significantly to the growth of consumer credit. A predecessor of the current micro loan, the amount at the end of the 1930s was generally limited to USD 300 (less than 50 percent of the US GDP per capita, the equivalent of about USD 6,500 in 2024) in cash and maximum legal interest rates were between 24 and 42 percent per year, depending on the particular state in the USA where the transaction took place. The supply of personal loans was encouraged “to combat the loan-shark evil, which had arisen because the usury statutes prevented the profitable lending of small sums at legitimate rates” (Young *et al.*, 1940, p. 1). This problem is current in numerous developing countries and microfinance was foreseen as the main tool to solve it.

Then, the need to reduce transaction costs and enhance the appraisal of risks was obvious in a competitive environment. The credit risk stemmed from the same asymmetric problem issues that we witness in microfinance today.

Another NBER study in instalment financing presented the problems that were experienced by the lenders (Chapman *et al.*, 1940). Credit providers were conscious that some attributes of the applicants were specific to bad borrowers and considered them in their subjective evaluation. Two broad indicators were important when judging a prospective credit risk: willingness and ability to repay the loan. Information on the income of the applicant, her net worth and other financial characteristics were predictors of the ability to pay back, while the willingness to pay depended on the applicant's character.

“On the basis of experience, and to some extent intuition, the loan officer decides which applicants are more likely to default than others or which loans are likely to involve collection costs so great as to render the transaction unprofitable” (Chapman *et al.*, 1940, p. 109). “Lenders need to know the relative importance of as many credit risk factors as can be isolated, and in making a final decision on a loan application the responsible officer must give due weight to each factor” (Chapman *et al.*, 1940, p. 137). The latter citation defines the main problem that credit scoring was supposed to solve using empirical methods, which is identifying risk factors and their weights.

Based on samples of ‘good’ and ‘bad’ clients coming from different financial institutions, Chapman *et al.* (1940) found the most significant risk factors: possession of a bank account, stability of employment, nature of occupation, permanence of residence, ownership of real estate and industrial affiliation. However, they made an important qualifying remark about the sampling that poses challenges for researchers and practitioners even today: “Since these borrowers had already passed through a selection process at the hands of credit men, the sample cannot be considered completely representative of the general run of personal loan applicants” (Chapman *et al.*, 1940, p. 111). This implied that the identification of risk factors was based on a previously screened sample of accepted applicants which became consequently good or bad credit risks. The sample could not include applicants who had been refused. Thus, the list of identified risk factors was based neither on the full population of loan applicants, nor on the universe of potential credit applicants.

One other NBER study (Plummer and Young, 1940) went beyond identification of credit risk factors and presented functioning credit rating systems. The use of such systems was not uncommon in the USA in the late 1930s. In some cases, a rating of good, fair or poor was

entered for each factor considered as an indicator of credit risk. The final rating represented the average of favourable and unfavourable indications. “In other cases a specific grade is entered opposite each item and the sum of the grades serves as the index of credit risk” (Plummer and Young, 1940, p. 136). The use of such rating systems is still common today, especially in micro and small business lending, but we note that subjective attribution of grades or weights to identified risk factors makes the technique distinct from credit scoring. Since empirics are not used directly in deriving the relative weights of risk factors, such techniques are generally referred as ‘credit rating’. Throughout this thesis, we will use the term ‘credit rating’ to refer to all techniques that aim to estimate the credit risk of a loan application using scorecards or algorithms derived without the use of proper statistical methods.

The work of Durand (1941), in yet another NBER study, marked the first important step in the development of the technique of credit scoring. The author used a large sample of 7,200 consumer loans disbursed by 37 financial institutions which included commercial banks offering personal loans, personal finance companies, automobile finance companies, and appliance financiers. Available borrowers’ attributes were copied from their loan application forms. These included age, gender, marital status, dependents in the household, stability of employment, permanence of residence, and other socio-demographic variables. Also, borrowers’ assets and liabilities, and loan characteristics such as amount and number of instalments were available. No information was collected on past credit behaviour or on “matters like physical or mental health, which are certainly germane to risk problem, but which obviously do not lend themselves to analysis in a statistical study of credit risks” (Durand, 1941, p. 20).

The crucial issue that Durand dealt with was the formulation of the concept of the credit scoring algorithm, which he called ‘credit-rating formula’. The formula combined the most important credit risk factors and respective relative weights. For the first time, identification of risk factors and calculation of weights was performed empirically. When lenders were scoring the applicants for credit, the weights of risk factors were computed, yielding a sum: the ‘credit-rating’ score. The score was used as the basis for accepting or rejecting loan applications. The advance and diffusion of the technique of statistical discrimination of populations (Fisher, 1936) played a key role in the emergence of credit scoring.

Intuitive-subjective rating formulas had been created before and used in financial institutions. Durand “experimented with deriving purely objective credit formulae by statistical methods” (Durand, 1941, p. 84). He pointed out precisely the advantages of credit scoring. Loan officers could assess ordinary loan applications faster and most of the routine evaluation work could be handled by less experienced and relatively low-salaried personnel. Considering that most developing countries suffer from the epidemic of brain drain, the advantages of credit scoring should appeal to many microfinance providers and supervising bodies.

Today the term ‘scorecard’ has replaced the expression ‘credit-rating formula’. In this thesis, however, we use the term ‘algorithm’, which comprises the scorecard and the set of instructions that are used, on the basis of the outcome of the scorecard, to take the decision to approve or refuse a loan request.

Durand identified several practical aspects to be considered in developing credit scoring algorithms. Two of them are particularly relevant for microfinance today: size of the sample and the timeframe. About the sampling size, he argued that though large samples were preferable, since collecting thousands of cases could be impossible or too expensive, a sample as small as one hundred good and one hundred bad loans might be adequate for statistical significance. Since many MFIs experience problems with data collection on a large scale due to bad databases or lack of management information systems (MIS), this suggestion of one hundred good and one hundred bad loans in the sample to develop a credit scoring algorithm is feasible within the microfinance reality.

About the timeframe problem, Durand remarked that risk experience associated with different factors may alter with the time because of the changing economic and social circumstances associated with that factor. One modern-day example of this could be employment stability. Changing employers too often has been commonly associated with workplace problems and subsequent financial uncertainty. However, in today’s work environment, changing employers could be associated with exceptional skills required for ad hoc, sophisticated and well-remunerated projects. Durand’s solution to this problem of the changing character of the risk factors over time was to limit the study to recent homogeneous periods. Good and bad credit risks being included in the algorithm development sample had to be recent. Further we use the

term ‘training sample’ to identify the set of good and bad credit risks used to derive the credit scoring algorithm.

Durand made the interesting remark that in practice it is difficult to make a precise distinction between confirmed good and bad loans. If the net revenue from a loan did not cover the expenses it generated, it was certainly a bad loan. If the principal and interest were repaid in full and on time, it was a good loan. The problem was with ‘grey’ cases where borrowers paid late. The financial institution collected penalty fees to be compensated for delinquency-related costs, such as reminders and specific supervision, but these did not always cover all costs. Since it was expensive to determine accurately at what level of delinquent credit behaviour a loan ceased to be profitable, Durand proposed several rules to define bad borrowers: “loan was more than 90 days delinquent; comaker [co-signer] paid all or part of loan after demand by bank; legal action was taken; loan was charged off” (Durand, 1941, p. 38). Currently, many microfinance institutions use the same rules when defining bad borrowers. In some markets however, where micro-borrowers make weekly repayments, 30 consecutive days delinquency – the equivalent of four missed instalments – is the preferred definition of a bad credit risk (Simbaqueba *et al.*, 2011).

Durand reiterated the remarks of Chapman *et al.* (1940) about the limitations of the sample due to initial screening of applicants by the loan officers. To overcome this problem, Durand suggested that financial institutions would initially use the scoring algorithm as a supplementary evaluation tool after the usual screening by the loan officers. Thereafter ‘experimental’ loans had to be disbursed by lowering temporarily and progressively the approval standards of the loan officers in order to gain new experience about the behaviour of applicants that were accepted by the credit scoring but would have been refused by the loan officers under normal circumstances. Such a solution could temporarily increase losses but should provide new experience for developing better credit scoring algorithms which would free the loan officer from the task of screening standard applications. Later on, researchers and practitioners proposed alternative techniques that are easier to implement. For example, Hand and Henley (1993) proposed the reject inference method. This involves several steps. Step one consists of inferring the credit risk class of rejected applicants – rejected applicants with profiles similar to bad credit risks were to be considered bad borrowers and rejected applicants with profiles similar to good credit risks were to be considered good borrowers. Step two

consists of including the profiles of rejected applicants in the training sample. Nevertheless, this method also does not completely resolve the problem, unless credit is initially provided to all applicants who show capacity to repay the loan they request, or at least to a representative sample covering all applicants, including those who show repayment capacity, but are generally refused due to suspicions of low willingness to repay the loan.

It follows from the discussion above that for developing a credit scoring algorithm a representative training sample of good and bad borrowers is needed. One needs to know their detailed profiles – the more characteristics the better. Data have to be structured, so that statistical methods can be used to identify risk factors and their weights to compose the algorithm. The resulting score is used to accept or reject applicants based on a certain cut-off. Obviously, statistics may contradict some subjective ways of thinking. For example, Durand (1941) had discovered that women tended to be good risks, much to the surprise of some lenders who were convinced of the contrary view. This has also been found to be true in microfinance. MFIs in many countries lend predominantly to women.

Durand found another counter-intuitive discovery – for personal loans, there was no direct relationship between the credit risk and the income level of the borrower, as long as income allows the loan to be reimbursed. This finding, highlighting the fact that not all poor persons are bad credit risks, stands at the foundation of microfinance (Dowla and Barua, 2006).

The revolutionary approach of Durand (1941) took some time to become known to scholars and financial institutions. That explains why there were no academic publications covering the topic of credit scoring till the 1960s.

2.3 The commercial era of credit scoring for consumer credit

The next stage in the evolution of credit scoring was its use on a commercial basis. Consumer lending expanded so fast in the USA, involving large segments of the public, to the point when lending organisations could not keep up properly with the demand. Myers and Forgy (1963) stated that increasing demand for credit pushed many financial institutions to expand beyond their capacities to train and maintain experienced loan officers. In such conditions, the role of credit scoring became critically important. In recent years, in many developing countries, for example Morocco, Bosnia and Herzegovina, and Nicaragua, micro lending experienced similar

unsustainable high growth, leading to over-indebtedness and consequent degradation of the market (Constantinou and Ashta, 2010). We think that accurate use of empirically-derived scoring algorithms by microfinance institutions could have played a positive role in reducing the default rate of borrowers.

Myers and Forgy (1963) developed several credit scoring and credit rating algorithms using one training sample of good and bad credit risks coming from one financial institution. This was different from Durand (1941) who had combined loans from different financial institutions. They used diverse statistical and non-statistical techniques to construct scorecards and then compared their predictive effectiveness.

Myers and Forgy (1963) enriched the conceptual framework of credit scoring by introducing the concept of ‘holdout’ sample, although they acknowledged that the idea was based on an unpublished thesis by Wolbers H. L. of 1949. The holdout sample was a sub-sample obtained by withholding a part of the available credit records before developing the algorithm. They developed the algorithm using the training sample and tested it on the holdout sample. In the current literature the term ‘test sample’ has replaced the holdout sample. It is used to validate the robustness of the scoring algorithm.

Being assisted by a computer, Myers and Forgy (1963) were able to experiment with different approaches to construct scorecards. In addition to the discriminant analysis used by Durand (1941), they employed stepwise regression, the (credit rating) method of equal weights for identified risk factors, and the ‘double-discriminant analysis’. Double-discriminant analysis gave the most satisfactory results. This method first required scoring of good and bad loans using the formula developed under the first approach – the discriminant analysis – then the credit scoring algorithm was redeveloped using only good and bad borrowers that received low scores – those with higher estimated credit risk. The purpose was to improve credit risk discrimination at ranges where the cut-off is fixed and many good borrowers and bad borrowers have similar scores.

Myers and Forgy (1963) found that a smaller number of risk factors – twelve in their case – will predict almost as well as all 21 identified relevant factors. This is an important finding when the cost of collecting information is relatively high, as in most microfinance

environments. The prediction power for each scorecard was measured using the point-biserial correlation coefficient which is recommended when one variable is artificially dichotomous – the risk class of known borrowers which can be either good (0) or bad (1) – and the other – the credit score – is continuous.

Myers and Forgy (1963) acknowledged the importance of the face validity of the credit scoring formula as perceived by the final users. The financial institution that provided the data for the research chose to implement one of the developed formulas, but not the most predictive one. The strongest formula by measure of the correlation coefficient was disregarded by the financial institution due to ‘bizarre’ weights of some risk factors.

Smith (1964) proposed a different approach to construct scoring formulas. He suggested adding together ‘bad account probabilities’ corresponding to each measured attribute (characteristic) of the applicant and considering the sum as the final credit score. These conditional probabilities measure the odds of a loan being a bad credit risk given certain attributes. The probabilities, all positive, were calculated using the training sample. If 25 in 100 borrowers who owned family cars were bad credit risks while those without cars were 50 bad risks in 100 and if 20 married borrowers in 100 were bad risks, while single borrowers were 40 bad risks in 100, then a married applicant with a family car would receive a tiny score of 45 over 100 [$25/100 + 20/100 = 45/100$], while a single applicant without a family car would score the double: 90 over 100 [$50/100 + 40/100 = 90/100$].

Smith (1964) introduced the practice of multiplying these probabilities by 1,000 for easier computing of the sum and clearer interpretation of the results. This multiplication by 1,000 was consequently adopted by the industry. Applied to the example given above, this practice would give 450 points for credit riskiness for the married applicant with a car and 900 points for the applicant who is single and without a car.

The methodology proposed by Smith (1964) is simple and clear because it uses simplifying assumptions and is thus not easily amenable to empirical investigation. Such methodology can still be used in credit granting but, due to its weak statistical foundations – impossibility to isolate the contribution of each factor to the credit risk – it should not be termed credit scoring. Properly addressing conditional probabilities requires know-how and software, which might

not be available in many microfinance institutions. Calculating 'bad account probabilities' and adding them up is a much easier task that can be done on paper. Using the methodology proposed by Smith (1964) in an MFI can have certain added value since it allows the loan officers to concentrate on the real risk factors and consider them in the process of loan appraisal. Adding up several 'bad account probabilities' is statistically incorrect, but such credit ratings will be nevertheless correlated with the real probability of default of loan applicants. The drawback of this methodology for microfinance is that calculated probabilities of default will be generally higher than real probabilities, thus many applicants can see their micro loan application refused. In microfinance, not giving a loan to a creditworthy borrower is not only a lost business opportunity for the MFI, but also a lost opportunity to create social impact. If the loan applicant cannot find similar financing with another lender, the potential micro-borrower loses the opportunity to develop the income-generation activity that could have helped lift the borrower's household out of poverty.

An even more serious weakness is found in the third technique (equal weights for identified risk factors) proposed by Myers and Forgry (1963) because it is logically questionable to allocate equal weights to each credit risk factor that would induce strong bias. However, the cost of such bias might be significantly lower than the opportunity cost of not using any scorecard. Many micro and small business lenders do not use credit scoring because statistics look too complicated to them. If simpler techniques can motivate micro lenders in using algorithms for credit granting, then benefits from reduction of transaction and delinquency costs would probably cover the risks associated with such a bias.

Smith (1964) made a valuable contribution in suggesting that the rejected applicants should also be subjected to the credit scoring formula in order to judge the robustness of the formula and possibly to overcome the bias which resulted in the first instance when differentiating between approved and rejected applicants. If the scoring algorithm rejected most of applicants that were turned down by the loan officers, then such algorithm could immediately replace the loan officer in treating standard loan applications. If, however, the algorithm failed to do so, it had to be used initially as a supplementary tool until the missing information on the credit behaviour of refused applicants would be gathered, as proposed by Durand (1941).

Weingartner (1966) attributed the increasing use of credit scoring in the USA to the growing availability of ‘electronic’ computers. He observed that financial institutions were still granting loans to applicants with higher credit risk, provided they were above the rejection cut-off, but these loans were smaller in amount and shorter in maturity. His study did not examine the aspect of risk-based pricing in the form of differential rates of interest charged to such low-scoring applicants, but the appearance of the practice of risk-based adjustments of loan conditions should be mentioned.

Weingartner (1966) highlighted the importance of performing pilot tests before credit scoring and similar rating tools are used by the credit institution. He suggested initially testing the developed credit risk estimation tools on newly emerging delinquent accounts to observe if they would have received low creditworthiness scores at the time of application. This easy-to-perform pilot test would either ensure higher confidence in the credit scoring formula if the test result were to be positive, or would raise the awareness of future users about a certain degree of risk in using the scoring formula if the test were to yield a negative outcome.

Weingartner’s (1966) work, for the first time in the literature, showed the importance of field trials. His procedure involved the use of credit scoring first by only a few loan officers or by only one branch out of the entire network. The procedure was intended for “training as well as for ironing out difficulties that arise” (Weingartner 1966, p. 52) and, in that sense, though not a constituent of the conceptual framework of the credit scoring, conducting field trials at small scale is a potentially useful optional procedure.

Post-implementation reports are an integral part of the conceptual framework of credit scoring. Weingartner (1966) proposed a continuous ‘barometer’ to measure the average score that would reflect the quality of new disbursed credits. The trend in scores of new borrowers would indicate the quality of newly engaged portfolio over time. In the same way the overall quality of refused applications could be observed. Significant fluctuations registered by the barometer would indicate on changes in the population of applicants – a warning sign. In microfinance institutions which use poverty scoring, but do not use credit scoring, the continuous ‘barometer’ proposed by Weingartner (1966) would measure the average score that would reflect not the quality of new disbursed credits, but the average poverty level of recently financed micro-

borrowers. A decrease in the average poverty level of new borrowers might indicate a mission drift.

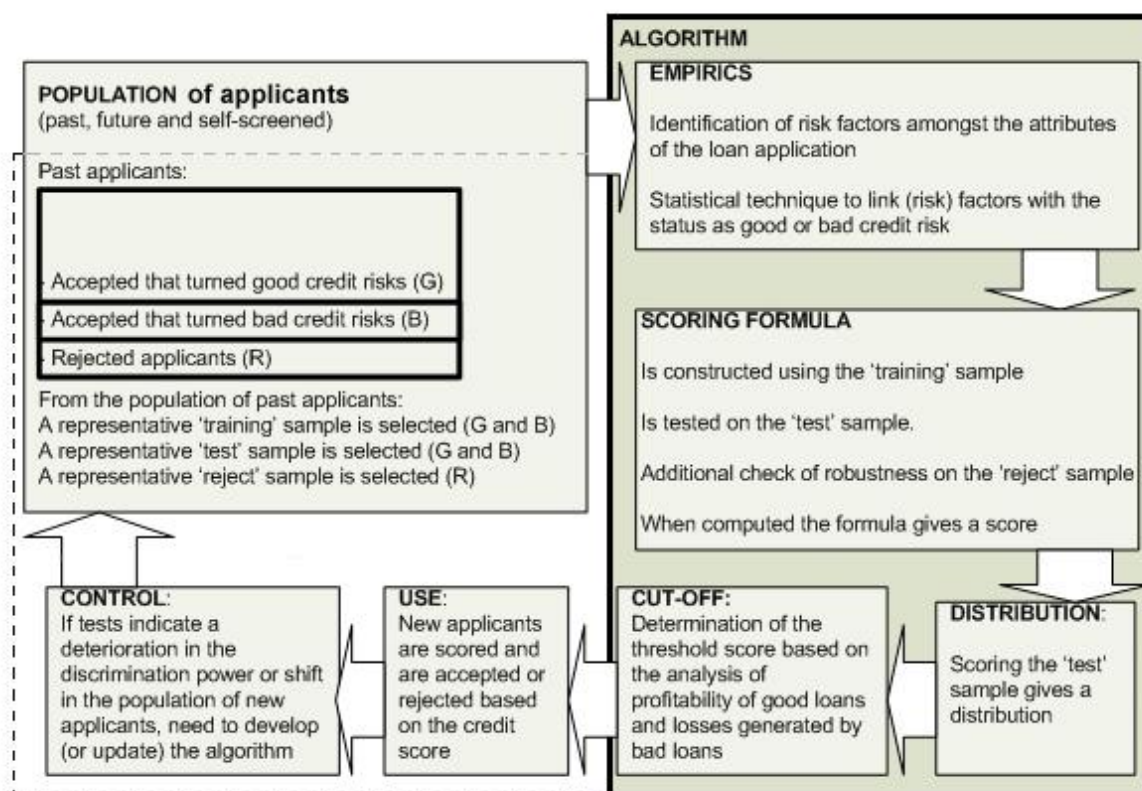
Research tendencies by the mid-1960s included efforts to build formulas that would predict the profitability of the loan, rather than the delinquency or default (Greer, 1967). After Hassler *et al.* (1963) provided evidence that current repayment records show strong ability to identify bad risks, Weingartner (1966) popularised the proposal to use the credit scoring technique in loan collection procedures. Collection scoring is useful in financing since it identifies current borrowers that are more likely to repay after being delinquent. In this way the financial institution can target them with appropriate collection actions and obtain certain return. Since the lender has already provided the borrower with a loan, collection scoring does not belong to the conceptual framework of credit scoring.

To sum up, it is clear that Durand (1941) laid the foundations of credit scoring but left unexplored areas, some of which were addressed by Meyers and Foggy (1963). Smith (1964) contributed to a practical use of credit scoring and Weingartner (1966) introduced pilot and post-implementation tests. Further improvement on their work and the description of the implementation and functioning of a credit scoring system in a financial institution in the USA was provided in a path-breaking paper by Boggess (1967). This provides a comprehensive picture to conclude that the main traits of the conceptual framework of modern consumer credit scoring were set by the mid-1960s. Today this framework can be used by MFIs interested in implementing credit scoring.

Boggess (1967) explained that the financial institution he studied implemented a credit scoring system in 1964 in which loan applications were automatically scored by a computer if policy requirements were respected. Within 24 hours the credit department was accepting or rejecting the loan application based on the credit score. Earlier, this task required up to one week. “The company cut bad debt losses enough to realise a [US]\$1.5 million profit improvement on more than [US]\$100 million in sales in the first full year of the system’s operation” (Boggess 1967, p. 121). Computerised MIS elements combined with the virtues of credit scoring gave the lender the possibility to operate procedures that adapted the strategy of the lending company to shifts in the applicant population. The financial institution was developing a new scoring formula every six months and was tracking changes in the weights of risk factors over time.

In Figure 3 we have captured the continuous process of development and use of credit scoring.

Figure 3. The conceptual framework of credit scoring as it existed during the mid-1960s



The 'Population' box in Figure 3 indicates the process of selecting the training, test, and reject samples. The 'Algorithm' box indicates the process of developing a credit scoring algorithm after required samples have been selected from the population and relevant data have been extracted and structured. This box includes several sub-boxes. These sub-boxes are separate for parametric credit scoring algorithms, which are based on scorecards (scoring formulas). For the non-parametric credit scoring algorithms, the sub-boxes ('Scoring formula', 'Distribution' and 'Cut-off') are combined.

The 'Empirics' sub-box indicates that, for developing the algorithm, a statistical technique has to be selected. All the statistical techniques that can be used to derive the algorithm belong to the group of multivariate statistical analysis. The algorithm attempts to model *post factum* the risk performance of the borrowers using certain information available at the time of loan appraisal. We assume that a perfect credit scoring algorithm, which identifies all the bad and all the good credit risks in the training and test samples, can be developed if the totality of

factors that determine the performance of these loans can be observed and measured, and the influence of each factor can be isolated and mathematically represented. Setting the rejection cut-off of the perfect algorithm is simple: it is the lowest score observed in good credit risks. All bad risks have scores below that level. When using only a few factors – the ones that can be accurately captured by the loan application and structured for computation purposes – the resulting algorithms are less accurate. In such conditions we can observe that certain good and bad credit risks have the same score or certain bad risks have higher scores than some good risks. Nevertheless, such algorithms have high utility as the share of bad risks outweighs the share of good risks in low scores and *vice-versa* in high scores.

The sub-box ‘Scoring formula’ indicates that all identified credit risk factors and their relative weights are grouped in a credit scoring formula – a scorecard. The scoring formula will be used to score future applicants. The robustness of the credit scoring formula is tested using the test sample and, if necessary, the reject sample. The ‘Distribution’ sub-box indicates that scores of past applicants that are already known to be good or bad credit risks (contained in the test and training samples) are compared with their credit risk status (good or bad). One should observe that bad credit risks systematically receive low creditworthiness scores and good credit risks systematically receive high credit scores. The credit scoring distribution indicates the share of bad credit risks to good credit risks for a specific score (or score range). The share of bad credit risks decreases as the credit score increases. The credit scoring distribution will serve as the scale by which future applicants will be judged. The ‘Cut-off’ sub-box refers to the selection of a cut-off score, which determines the threshold for processing loan applications. Applicants with creditworthiness scores above the cut-off will be accepted because they are considered good credit risks. Applicants with creditworthiness scores below the cut-off will be refused because they are considered bad credit risks. The conceptual framework of credit scoring, as it is presented in Figure 3, deals with one cut-off, and this cut-off is for both, approving and rejecting loans. The concept of a cut-off score can be more nuanced in microlending as well as in other credit segments. One cut-off score can be used for automatic approval, while other cut-off score can be used for automatic rejection. Loan applications that fall in between are analysed by competent loan officers who individually, or as part of a credit committee, decide if the loan application is approved or rejected. Depending on the borrowed amount or loan tenure, the auto-approval cut-off, as well as the auto-rejection cut-off, can increase or decrease.

The reject sample is used to observe if the credit scoring algorithm screens out most of the previously refused applicants.

The ‘Use’ box indicates that when credit scoring is used, the final credit decision has to be consistent with the outcome of the credit scoring algorithm. Overrides should not happen. If the loan officer disregards the output of the credit scoring algorithm, the decision has to be justified. The results of such decisions have to be analysed, especially when the credit risk of accepted through override applicants is revealed.

The ‘Control’ box is to check if the algorithm is still appropriate over time. If tests indicate deterioration of credit risk discrimination power or shifts in the population of applicants, it is necessary to develop a new credit scoring algorithm. Manual adjustments of weights of the characteristics included in the credit scoring algorithm, to increase the degrading credit risk discrimination power, are not in line with the principles of statistical multivariate analysis, however, temporary improvements in the credit risk estimation can be achieved.

Once the accepted applicants pay back their loans or register serious delinquencies, they reveal their real – good or bad – credit risk class. Such new cases come to enrich the population of recent applicants with known credit risk. These cases should be used afterwards to develop new, more accurate credit scoring algorithms to replace the old ones. In fact, credit scoring algorithms built using artificial intelligence principles can ‘learn’ and adjust themselves constantly as new experience of using credit scoring becomes available. In such cases, the ‘Algorithm’ box in Figure 3 covers also the dashed area – the boxes ‘Use’, ‘Control’ and ‘Population’.

2.4 Credit scoring for corporate lending

While credit scoring was the exclusive domain of consumer credit, Altman (1968) employed the statistical discriminant analysis approach to predict corporate bankruptcy using financial ratios as credit risk factors. He did not take into account other important attributes such as business-demographic characteristics like the age of the business or professional experience of the management. Other potential risk factors such as the purpose of the loan, maturity, and guarantees were not considered either. In spite of these limitations, Altman’s contribution to the conceptual framework of credit scoring is important as it opened it for use in business loans.

Altman (1968) enlarged the framework to include firms in addition to individuals. Obviously, the attributes that describe firms are different, although some overlap might exist.

Orgler (1970), inspired in part by the work of Altman, focused on the use of the credit scoring technique in current commercial loans. His scope excluded loan approval, addressing only the periodic review of the quality of already disbursed loans. He made the interesting remark that business borrowers form less homogeneous populations if compared with consumer borrowers. This problem had not been addressed in the academic literature before. Since then, the condition of homogeneity of the targeted population, considered by practitioners and academics to be implicit in consumer credit, has become part of the framework of credit scoring. Orgler (1970) concluded that business borrowers were so diverse and their loan products so varied in terms of maturity, amount, and collateral, that the application of a credit scoring model for approval of loans would be less appropriate. The main advantages of the technique were seen in releasing loan officers' time from routine evaluation of all current credits and allocating it to the small proportion of loans that would be identified by the scoring tool as being at risk of default.

As briefly outlined by Altman (1968) and in more detail by Orgler (1970), the use of credit scoring to measure the evolution of credit risk over the course of a loan was a new and valuable approach for the industry. This was particularly important since business loans typically have longer maturities, and changes within the firm during the loan period could significantly affect its credit risk. During the loan repayment process, new information, especially on repayment behaviour, is regularly received to update the borrower's profile. Credit scoring algorithms can integrate this new data to predict defaults more accurately. However, since credit risk can no longer be avoided once the money has already been lent, this approach falls outside the scope of the credit scoring conceptual framework. Similarly, we exclude the collection scoring proposal by Weingartner (1966), as described in the previous subchapter, from the credit scoring framework.

The distinction between consumer and business loans tends to lose its significance in microfinance. Since microcredit addresses generally poor and self-employed people – situation in which the borrower is at the same time the person applying for the loan, the household of this person which helps with the business, and this person's small income-generation activity,

all in one. The person – the applicant – and the firm – the business entity or also known as moral person – are in general evaluated together in microfinance. Several scholars, including Orgler (1970), cited the dissertation of Ewert of 1968 that proposed a credit scoring formula to be used by wholesale distributors in granting trade credit to retail stores. As the stores were mostly sole-proprietor small firms needing trade credit in amounts similar to consumer credit, the formula used a combination of risk factors describing the company, legally responsible for the loan, and the owner – the person owning and managing the retail store – to estimate the probability of default of the retail store.

Taking into account the work of Orgler (1970) and the cited dissertation of Ewert, it is noted that the profile of the owner of the business as well as the profile of the business itself may be important in predicting credit risk, especially in small companies where personal and business property confounds. This is certainly the case of microlending. This is also the case in larger but informal business in which the boundaries of the assets and responsibilities of involved natural persons and the boundaries of the moral persons – the businesses – are blurred.

2.5 Institutionalisation

The early 1970s saw the credit scoring industry grow. Fair Isaac and Company (FICO), which sold the first commercially built credit scoring algorithm in 1958, started its collaboration with Wells Fargo – a major financial institution in the USA. The credit scoring provider was prospecting the exportation of the technique to Europe (Fair Isaac Corporation, 2012). An increasing amount of academic literature dealt with different practical and theoretical topics related to the credit scoring technique. Emphasis was put on costs and net present value of loan repayments (Edmister and Schlarbaum, 1974), on best statistical techniques to be used (Muchinsky, 1975a), as well as on better definitions for good and bad credit risks (Muchinsky, 1975b).

Some serious works were addressing the use of credit scoring in low-income populations in the USA. Tabor and Bowers (1977) stated that then-existing credit scoring systems were not appropriate for evaluating low-income consumers, while Sexton (1975) found that only a few risk factors differentiated between high-income and low-income households, and thus could not conclude that specific algorithms for different income categories were necessary in the country.

In microfinance, the debate on the suitability of credit scoring is far from over. There are academics (Schreiner, 2000; Rayo Canton *et al.*, 2010; Bumacov *et al.*, 2014) and practitioners (Kortenbusch and Hauser, 2010; Simbaqueba *et al.*, 2011) who argue in favour of the adoption of credit scoring by the MFIs while others are against (Balke, 2005).

The debate over the use of credit scoring in low-income populations in the USA was triggered by the report of the US National Commission on Consumer Finance (1972), which had questioned the feasibility of a ‘credit scoring system’ applicable to low-income consumers and concluded that factors most likely to discriminate the credit risk of low-income consumers were excluded from standard loan application forms.

Muchinsky (1975b) found that two opposite aspects of the borrower’s repayment behaviour were critical to its classification as good or bad credit risk. One was delinquency. The other was the early repayment of the loan. A premature reimbursement was susceptible of making the credit account unprofitable because it led to the loss of potential interest. Accrued interest on a loan, paid regularly, should exceed the cost of the funds the financial institution has provided to the borrower. This positive margin, resulting from the difference between the price the borrower pays for the loan and the real cost of the loan, should offset the loan transaction cost before generating profit for the financial institution. If the borrower repays the loan much earlier than expected, there is a risk that the loan transaction cost is not fully offset, or that maturity mismatch engenders extra costs for the lender, both leading to losses for the financial institution. Although the borrower is not delinquent, anticipated repayment of the loan can lead to losses for the financial institution. This perspective, highlighted by Muchinsky (1975b), modified the perception of what constituted a bad credit risk. Repayment ahead of schedule, as bad credit behaviour, can be included in the definition of bad credit risk along with late repayments, however, the profile of borrowers who repay early should be radically different from the profile of delinquent borrowers. In such a situation, separate algorithms should be developed: one that predicts the probability of the loan applicant to register repayment delinquencies and a separate one that predicts the early repayment of the loan by the same applicant. Both, the credit score and the ‘early repayment’ score need to be considered when deciding if to approve a loan application. The lending industry has found substitute solutions for dealing with financial losses associated with early repayments. One solution is charging a loan appraisal fee. Charged on all loan applications that look viable, the fee is meant to: offset

the application appraisal cost; dissuade bad borrowers from applying for loans; and avoid charging indirectly the successful borrowers the cost of appraisal of non-financed applications. Another solution for dealing with financial losses associated with early repayments is the early repayment fee – additional charges that the borrower pays when the loan is reimbursed ahead of the repayment schedule.

The Consumer Credit Protection Act of 1968 facilitated the extension of credit to low-income clients and added legitimacy to the concept of credit scoring in the USA. The Equal Credit Opportunity Act of 1974, with the amendments of 1976, had also notable implications. This law prohibited discrimination in the granting of credit on the basis of race, religion, gender, marital status, and age. These ethical concerns were formalised in a legal setup and in this way constrained the conceptual framework of credit scoring in the USA.

The in-house know-how character of credit scoring systems used by financial institutions represented an increasing problem for scholars, who found it difficult to relate and research how well the US industry incorporated new tendencies and legal requirements into practice. The new regulation in the United States required that statistically sound scoring systems be constructed using empirical methodologies, but no precise standards were imposed. The hypothetical obligation to demonstrate the soundness of a scoring system in court made scholars focus on different technical aspects and assumptions that were ignored before, as long as the algorithm showed evidence of credit risk discrimination in the test sample or in practice.

In the absence of case studies, Eisenbeis (1978) analysed the credit scoring systems developed by academics at that time, hoping that these reflected the credit scoring algorithms in use by lenders. Since the majority of credit scoring formulas were developed using discriminant analysis, he pointed out to the limitations of the technique and warned the public on the risks of ignoring the inherent statistical assumptions.

With the emergence of credit bureaus selling information on past credit performance of potential borrowers, the cost of extra information was considered in different credit granting schemes (Eisenbeis, 1978). If a scoring formula predicted credit risk accurately using fewer risk factors, as observed by Myers and Forgy (1963), there was no point in paying for extra information that was sold by information traders such as the credit bureaus. On the other hand,

if additional information could help discriminate better loan applications near the cut-off limits, then extra costs were mostly justified. Academics were investigating how credit scoring algorithms could accommodate these options.

Currently, credit reporting is either new in many developing countries or non-existent (World Bank, 2017). More than that, in countries where private or public credit reporting systems exists, these exclude microfinance institutions. This is unfortunate because credit reporting data are widely used in credit scoring algorithms.

Ang *et al.* (1979) were among the first to build a non-parametric credit scoring system. They applied the decision tree technique to a training sample with good and bad credit risks. The result was a tree-like scheme where risk factors did not have weights but acted like nodes and branches indicating at the end of the tree-like scheme if the applicant was a potential good or bad credit risk.

Use of automatic interaction detector analysis confirmed that the relationships between late payments and some borrower attributes were nonlinear (Ang *et al.*, 1979). Take the example of a continuous variable such as the age of borrowers. Most would expect to see the credit risk diminishing with age, as borrowers become more experienced. In some credit segments, however, older borrowers pay better until a certain age when their credit behaviour starts to worsen and resembles the behaviour of young borrowers. Linear credit scoring models have a disadvantage in such situations if the relationship between the age of the borrower and the credit risk is assumed to be linear along the entire age range, while this is true only for some segments.

Since the technique of decision trees belongs to the class of statistical multivariate analysis, the conceptual framework of credit scoring did not change. We note that besides discriminant analysis and regressions, which became popular at the end of the 1970s, a myriad of parametric and non-parametric statistical techniques was used in identifying good and bad credit risks (Häußler, 1979).

We conclude that by the end of 1970s, credit scoring was a recognised technique and a growing industry. The concept of credit scoring found its first use in Europe, being implemented by

FICO in a bank in 1977 (Fair Isaac Corporation, 2012). The company had by that time delivered approximately five hundred systems to approximately two hundred customers, including half of the fifty largest US banks, according to the testimony of William Fair, that time head of FICO, during hearings required by a Senate Commission (U.S. Senate, 1979).

2.6 New dimensions of credit scoring

From the perspective of the 1980s, looking back at the adoption in 1974 in the United States – by far the leading market for credit scoring – of the Equal Credit Opportunity Act, which was originally perceived as a threat to credit scoring, we have a different view. Since the use of discriminatory factors was prohibited, many feared an overall reduction in predictive power of scoring systems in spite of some research findings (Nevin and Churchill, 1979) that showed no impact of the constraints imposed by the law. However, since judgmental systems were strongly criticised as subjective and thus prone to stronger discrimination by loan officers, credit scoring had to gain. Credit scoring was objective by definition and, under the new law, was considered respectful of ethical issues.

Capon (1982), one of the strongest opponents of the use of ‘brute force empiricism’ in credit scoring, remarked that algorithms in use in the USA included factors with no obvious or possible logical relationship to the creditworthiness of the applicant. Other factors directly related to the capacity to pay back a loan, such as the income of the applicant, were often ignored. With computers becoming more popular and powerful, and statistical packages becoming more user-friendly and affordable, many practitioners engaged in a ‘wild West’ conquest of predictive risk factors or in a search for surrogates of prohibited factors, which were considered by the US law as discriminatory.

In parallel, the credit bureau industry grew, supported by continuous expansion of the consumer credit market. Databases expanded in volume and complexity of gathered information. In 1981, FICO introduced the first credit bureau score (Fair Isaac Corporation, 2012). For an additional fee, the inquiring financial institution would henceforth receive not only the existing credit record of the applicant but also a credit score. The ‘bureau score’ could be used solely or in combination with the institution’s appraisal result in deciding whether to grant the credit or not.

A new concept called ‘expert system’ was supposed to have serious implications in the credit business, particularly in consumer credit. Backed up by developments in the ICT industry, expert systems were software designed to imitate the way of thinking of a human expert (Holsapple *et al.*, 1988). However, the expert system technique remains judgmental and not empirically founded – a *sine qua non* condition for a credit scoring system. Nevertheless, the advantage of ‘cyber loan officers’ consisted in the possibility of providing a credit decision in real time or much faster than a loan officer, leaving to the human loan officer the task of treating non-standard applications. Cyber loan officers have strong potential in cutting transaction costs in microfinance, especially the transaction cost of potential borrowers located in remote areas where it takes a lot of effort and time to get to a branch of a financial institution.

Credit scoring principles progressively invaded other banking and non-banking sectors such as detection of fraud with credit cards (Rutledge, 1996; Bolton and Hand, 2002), direct marketing (Thrasher, 1992), or credit performance (Crook *et al.*, 1992). It is noteworthy, however, that the use of the principles of credit scoring outside credit granting remains beyond the scope of the conceptual framework of credit scoring. On the other hand, the application of the credit scoring technique in approving loans to small and medium businesses (SMEs) and mortgage loans enriched the framework. In 1995, FICO developed a credit scoring tool for granting credit to SMEs (Fair Isaac Corporation, 2012). Before 1995, it is assumed that credit scoring had been applied by lenders to consumer credit mainly, although Altman (1968) demonstrated that the principles of credit scoring can be applied to business lending. Consumer credit has the advantage of being a mass-market segment involving relatively small, frequent loan transactions with relatively high levels of delinquency and defaults. Many lending institutions could gather enough bad loan cases for custom-built credit scoring algorithms. Other institutions could trust or were tempted to trust off-the-shelf algorithms for credit scoring consumer loans. The relatively small amounts of consumer loans, if compared to business or mortgage loans, could also explain why consumer credit remained the almost exclusive segment of application of credit scoring. If one can argue that businesses are more heterogeneous than consumer credit clients, and lending institutions feared the use of credit scoring in less heterogeneous credit segments, then this logic doesn’t explain the slow adoption of credit scoring in mortgage lending. Being long-term credits, mortgage loans require significant time to reveal their good risk nature. A delinquent mortgage loan can be classified immediately as bad credit risk, however, to classify it as a good credit risk, the borrower needs to repay the

entire loan or at least a significant portion of the loan without significant delinquencies. The lack of sufficient good and bad credit risks eligible for statistical treatment could explain the slow adoption of credit scoring in other credit segments which involve larger loans or loans with longer maturities.

For developing the credit scoring algorithm for SMEs in 1995, Fair Isaac Corporation (2012) used the concept of ‘pooled data’. This means that several financial institutions contributed with data for FICO to have enough records to develop the credit scoring algorithm for SMEs.

2.7 The microfinance era

In many countries around the world the informal and semi-formal sectors represent an important share of the GDP (Harriss-White, 2003). There is a significant number of people employed in the informal economy who need financial services. Microfinance is a possible answer to a majority of these needs.

As microcredit evolved from group to individual lending, Viganò (1993) studied the applicability of credit scoring in less developed countries proving the usefulness of the technique in granting credit to small and micro firms in Burkina Faso. After consumer, mortgage, SME and corporate lending, credit scoring entered microfinance. It was later recognised as one of the important techniques that may affect microcredit (Rhyne and Christen, 1999).

Schreiner (2000) concluded that credit scoring for microfinance can work, but highlighted certain differences compared to its use in mainstream finance. The most important difference he found was in the information available for decision making in financing poor borrowers. In a typical microfinance setting, information is usually qualitative and informal, while credit scoring algorithms require inputs based on quantitative variables. The new challenge of credit scoring was then to adapt to this constraint.

Unfortunately, the adoption rate of credit scoring in MFIs remains low and current debates suggest that credit scoring history repeats itself in microfinance instead of immediately flowing with the mainstream. Repetition of past mistakes generates inefficiencies. These mistakes can

be avoided if microfinance institutions apply the conceptual framework presented in this chapter.

At the same time, microfinance has permitted scoring techniques to go into new areas. It is in the context of microfinance that the concept of poverty scoring emerged (Schreiner, 2010). Similar to credit scoring, poverty scoring estimates a person's chances of being poor without measuring her income and wealth, but observing several easy-measurable factors.

Since poverty scoring does not estimate the credit risk, it lies outside the conceptual framework of credit scoring. Nevertheless, the conceptual framework of poverty scoring is identical to that of credit scoring except for the scope of the technique, the definition of the 'bad' applicant and the profile of the applicant.

2.8 The conceptual framework of credit scoring

By synthesising a wide range of insights from the literature review, this thesis develops a comprehensive conceptual framework for credit scoring. This framework is designed to be adaptable for use in microlending as well as in any homogeneous credit market, whether established or emerging. With the adoption of this framework, MFIs can avoid repeating historical errors and mistakes – the historical recurrence – thereby accelerating the integration of credit scoring into the mainstream microfinance sector.

The conceptual framework of credit scoring includes:

- the scope;
- the population;
- the definition of bad credit risks;
- the profile of the credit risk;
- statistical multivariate analysis;
- the algorithm; and
- ethics.

These components of the conceptual framework of credit scoring are described below.

2.8.1 The scope of credit scoring

The scope of the technique of credit scoring is to help manage the problem of granting credit. Credit scoring relies on empirically-derived algorithms that classify loan applications as good or bad credit risks using the known profile of the prospective credit transaction – a list of pre-determined characteristics describing the future borrower and the proposed loan transaction to be observed and considered by the credit scoring algorithm. Loan applications are formulated by loan applicants who necessarily belong to a homogeneous and massive statistical population. The algorithm is derived using a statistical multivariate analysis technique that allows identifying risk factors and respective weights using a training sample that is composed of recent borrowers whose status as good or bad credit risk is known. The pre-determined profiles of these borrowers are also known. The assumption is that future borrowers will have a credit behaviour identical, or similar, to that of past borrowers with similar profiles. Statistical significance and representativeness have to be respected. Due to the fact that past borrowers have already been screened by loan officers during approval, the population with known credit risk status is biased. If the credit scoring algorithm doesn't screen out a large proportion of applicants who were refused by loan officers, a sample of such applicants, who show capacity to repay requested loans, has to receive credit in order to obtain new experience on their credit behaviour and incorporate it in a new credit scoring algorithm. Before that, the current credit scoring algorithm should not be used as a sole bad credit risk screening method, but rather to complement the work of the loan officer. The algorithm's robustness is confirmed using a representative test sample and a sample of rejected applicants. The algorithm's economic significance is also estimated. Economic significance is different from statistical significance because the cost of misclassifying a true bad credit risk is several times higher than the cost of misclassifying a true good credit risk. If economic significance is satisfactory, the credit scoring system is implemented and used in the process of screening off loan applicants. Results of the use of credit scoring are regularly verified through post-implementation reports, unless the algorithm is able to learn constantly from newly available experience.

2.8.2 The population

The term 'population' here has the meaning which is used in statistics – a set of similar items or events which is of interest for the statistical analysis. In the context of the conceptual framework of credit scoring, the population is technically comprised of loan applications. In

reality the population is composed of subjects interested in the loan products of the financial institution and who are qualified to apply for loans. Subjects can be natural persons (individuals), households, or legal persons (enterprises). In micro and small business lending the subject is a combination of the household head, her household and her business. Even if the loan is taken by a small business which is registered as a limited liability enterprise, meaning that the liability of the owners of the business is limited to the assets of the business, the lender will systematically engage the responsibility of the owners by requiring a personal pledge to guarantee the repayment of the loan by the enterprise.

The population should be homogeneous for statistical reasons and large for statistical and economic reasons. Achieving greater homogeneity means reducing dispersion or eliminating certain categories of borrowers – fact that reduces the size of the population. Increasing the size of the population for statistical reasons related to the law of large numbers is done mostly at the expense of homogeneity. Equilibrium between homogeneity and size of the population can be reached by adjusting application policies and loan characteristics. For example, a financial institution can issue micro loans only to microentrepreneurs, while individuals who are not entrepreneurs can apply for consumer loans only. Loan products can have similar sizes and maturities but consumer loans target personal needs while micro entrepreneurial loans target business needs.

In a paper (Bumacov, 2013), we argue that revolving personal credit is extensively used in France by microentrepreneurs who cannot get a business credit from a bank. In this case the targeted population is composed of individuals who need funds for their consumer needs, but the credit product is also used by the microentrepreneurs. To improve the credit risk discrimination power of credit scoring algorithms used in granting revolving consumer credit, the consumer borrowers need to be separated from the entrepreneurs and distinct credit scoring algorithms need to be developed. The gains in risk discrimination power, however, might not be worth the effort.

2.8.3 The definition of bad credit risks

The definition of bad credit risks represents the rule used to identify credit risks to be avoided in the future with the help of the credit scoring algorithms which will be developed using this rule. Defaulted loans are the primary bad credit risks. However, loans do not need to default to

generate losses for the lending institution. Frequent delinquencies or a single serious delinquency can make a loan unprofitable or prompt the lender to classify the loan as a bad credit risk – such loan transactions to be avoided in the future. Basically, financial institutions may refuse to issue new credit to certain applicants after a disappointing experience with their previous loans, which, although not in default, had frequent or severe delinquencies. Such disappointing loans can also be considered bad credit risks. While loan profitability is the best indicator for classifying a loan as a good or bad credit risk, delinquency serves as a strong proxy for identifying bad credit risks. Generally, good credit risks are simply those that are not bad, though separate definitions of good credit risks may exist in credit scoring.

We have already discussed that a loan can become unprofitable in two distinct situations: when the borrower is delinquent or defaults, and when the borrower repays the loan ahead of schedule. For credit scoring purposes, unprofitability must originate from borrower delinquency, not early repayment. Delinquency doesn't always result in losses for the lender. In some cases, a loan may become more profitable than average because the borrower was frequently in arrears and paid corresponding penalties. However, there are also cases where initial profitability due to penalties ends in default. Borderline cases – where similar loan profiles are classified as good credit risks due to frequent delinquencies without default, and bad credit risks due to frequent delinquencies followed by default – can diminish the discriminatory power of credit scoring algorithms developed from such data. Since delinquency is the common factor in the two borderline cases described above, defining bad credit risks based on delinquency allows the credit scoring algorithm to more accurately identify future credit transactions likely to experience delinquency.

We can also have borderline cases – good and bad credit risks are very similar in their profiles – when an institution fixes a cut-off, in terms of maximum delinquency, to separate good credit risks from bad credit risks. It is common in microfinance to consider loans that reach 30 consecutive days in arrears as bad credit risks. If an MFI considers all loans that reached 30 days in arrears as bad credit risks, and all that did not reach 30 days as good credit risks, including loans that were only 29 days delinquent, then loans that registered their higher delinquency 29 days will be classified differently from loans that were 30 days delinquent. It is possible that the profiles of such borderline credit risks are very similar, and it is only by chance that some registered 29 days in arrears while others registered 30 days. Being classified

as good and bad credit risks randomly, these records will induce some noise in the credit scoring algorithm by cancelling out the effects of relevant characteristics. It could be argued that having a grey zone around the cut-off might improve the predictive power of the credit scoring algorithms. An important fact to consider is that loans are usually repaid in monthly instalments. These instalments include a portion of the principal to be repaid and the accrued interest to be paid. If a borrower is already one month in arrears, then the new instalment which becomes due the following day complicates much the situation of the delinquent borrower. The due amount is already composed of two instalments, plus the penalties for the missed payment. From this perspective the difference between a borrower who is 29 days in arrears and the one who is 30 days in arrears seems significant and the more such borderline cases are used for the development of credit scoring algorithms the better will be the algorithms in predicting which applicants will register 30 days in arrears and which will do the necessary, often the impossible, to repay the due instalment and stop the delinquency just before reaching the 30-days threshold. The only way to decide which approach the financial institution needs to take is to develop separate credit scoring algorithms (with grey zone around the cut-off and without) and chose the one which has the greatest credit risk discrimination power.

Institutions can use the delinquency roll rate analysis, called also delinquency transition analysis or delinquency migration analysis, to decide at which number of days past due to set the cut-off for the bad credit risk definition. The roll (transition or migration) rate is the proportion of credit risks which improve, worsen, or do not change their delinquency status from one period to another – the period usually being the month or other interval at which the borrowers repay their loans.

Another way to see the delinquency roll rate is to observe how late was the borrower in repaying one instalment – considered current instalment – and compare it with the delay registered in repaying the next instalment. Based on the combination: current instalment state of delinquency with next instalment state of delinquency, all such instances can be spread over a range of buckets which appear when current instalment state of delinquency and next instalment state of delinquency are used to create a matrix. Table 4 presents such an example produced using the repayment behaviour of microenterprise borrowers which took their first loan with a microfinance institution operating in a country from the Eastern Mediterranean.

We observe that in 63.5 percent of cases (column 2, row 1), if the borrower is either not late or has a minor delinquency of no more than 7 days in repaying one of the instalments, the borrower's repayment behaviour will not worsen when repaying the next instalment. In the remaining 36.5 percent of cases (column 2, sum of rows 2 to 7), the borrower's repayment behaviour will worsen when repaying the next instalment. To calculate these percentages, which represent probabilities, the number of cases in each bucket must be converted into percentages of the column totals. All interpretations of delinquency roll rates in such grids should be conducted column-wise.

Table 4. An example of delinquency roll rate matrix

Row #	State of delinquency of next instalment	Current instalment state of delinquency (calendar days)						
		0 - 7	8 - 14	15 - 30	31 - 60	61 - 90	91 - 120	121+
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	0 – 7 days	63.5%	38.0%	11.7%	6.7%	5.5%	5.5%	4.5%
2	8 – 14 days	10.1%	24.3%	7.9%	3.3%	2.4%	2.1%	1.7%
3	15 – 30 days	11.7%	19.4%	30.8%	15.9%	12.4%	20.6%	16.1%
4	31 – 60 days	14.6%	18.0%	47.2%	18.6%	11.8%	6.6%	5.9%
5	61 – 90 days	0.1%	0.2%	2.5%	43.7%	11.3%	5.4%	3.0%
6	91 – 120 days	0.0%	0.0%	0.0%	11.7%	49.7%	21.0%	8.4%
7	121+ days	0.0%	0.0%	0.0%	0.1%	6.9%	38.8%	60.3%
8	Total	100%	100%	100%	100%	100%	100%	100%

In the example presented in Table 4, we can observe that if a borrower reaches 15 to 30 days in arrears in repaying one instalment, chances of registering a similar delinquency when repaying the next instalment are 30.8 percent (column 4, row 3). The chances of worsening repayment behaviour and registering a more severe delinquency when repaying the next instalment after 15 to 30 days in arrears are 49.7 percent (column 4, sum of rows 4 to 7). This significant percentage should alert the MFI that when a micro-borrower from the analysed population reaches 15 to 30 days in arrears, the likelihood that this delinquent behaviour will worsen is almost 50 percent.

Usually, as the delinquency of a loan increases, the collection efforts of the financial institution also increase. The costs associated with increased monitoring and collection efforts rise as well. Many financial institutions decide to implement collection scoring – a technique inspired by credit scoring – which helps loan officers and collection personnel choose the most appropriate strategy for dealing with a delinquent borrower. Collection scoring helps identify a strategy with the best chances of succeeding in collecting the due amount, while also considering costs,

potential losses, and benefits. Information asymmetry is typically high in such cases, and the financial institution seeks to understand the underlying causes of the delinquent behaviour that is not improving. Collection scoring helps reduce this information asymmetry. If the causes of missed payments are temporary, the best collection strategy may be to wait.

The microentrepreneurial environment typically operates with high commercial margins, but micro-borrowers also face high revenue volatility. A similar situation applies to many farmers. While their profitability is relatively high when measured over a longer period, their cash flows tend to be uneven, influenced by factors such as the seasonality of crops, payment terms often exploited by wholesale buyers, the receipt of occasional subsidies, family events, and weather conditions.

Microfinance institutions and credit organisations that serve populations with volatile revenues, such as families of migrant workers who send money home every three to four months, might define bad credit risk based on the number of times a borrower is in arrears, rather than the maximum level of delinquency. For such institutions, being in arrears for more than 30 days once does not trigger the bad credit risk flag. However, being in arrears for 30 days or more on three separate occasions within 12 months would trigger the bad credit risk flag.

Since significant delinquencies are a precursor to default, any definition of bad credit risk based on substantial delinquency levels should lead to credit scoring algorithms that can effectively discriminate between different levels of credit risk. It is important to reiterate that if a loan experiences a significant delinquency in the early months, triggering the bad credit risk flag, the loan will be classified as bad credit risk. However, a loan that does not register any delinquencies in the initial months cannot automatically be considered a good credit risk, as the borrower still has a substantial portion of the loan to repay. A loan is classified as a good credit risk only if it does not trigger the bad credit risk flag (or meets the institution's criteria for a good loan) throughout the loan's duration, or at least when 80-90 percent of the principal has been repaid.

2.8.4 The profile of the credit risks

Credit risks, which can be classified as good, bad, or unspecified in the context of this thesis and credit scoring, encompass more than just the loans taken by the target population from the credit institution. The credit risk profile represents the characteristics of both the loan and the borrower, as assessed by the credit institution at the time of loan approval – essentially, when the institution accepts the credit risk associated with the loan transaction.

Microentrepreneurial credit risks likely have the most diversified profiles. This is because the applicant's profile is crucial in predicting credit risk, but so are the profiles of the applicant's household and business. The nature of the transaction also influences the credit risk. In microfinance, since the business is often an extension of the household, the characteristics of the household are just as important as the personal traits of the entrepreneur.

In consumer lending, the borrower's profile is typically the sole consideration for deciding whether to approve the loan. In corporate business lending, the company's profile is the main factor, with the profiles of owners or managers usually having little to no direct influence on the credit decision. It is assumed that company governance is provided by the board of directors, whose competences and powers extend beyond those of the owners.

The profiles of microentrepreneurial credit risks are composed of at least five categories of characteristics:

1. sociodemographic;
2. business-demographic;
3. consolidated financial information;
4. loan transaction characteristics; and
5. past credit behaviour.

Past credit behaviour is not a category per se, it represents the profile of the applicant – person or business. Due to the high importance of the past credit behaviour in predicting the future credit behaviour of the applicant, and because not all applicants have a known or proven past credit behaviour, it can be considered a separate category.

Sociodemographic characteristics

Sociodemographic characteristics describe the microentrepreneurs and often their households. The microentrepreneur should be the one managing the business and controlling the use as well as the repayment of borrowed funds. The age of the microentrepreneur is thus important in predicting the credit risk of the loan requested by the microentrepreneur. Education, working and entrepreneurial experience, experience in the current business sector, skills, and financial literacy are also important in predicting the credit risk. Not all such characteristics will show a significant association with the credit risk, but the profile of the entrepreneur, in general, is a factor influencing the credit risk of requested loans. Marital status is also important in predicting the credit risk as well as the characteristics of the entrepreneur's household. The number of dependants, the number of household members with additional revenues, the type, location, and property status of the house are in general associated with the credit risk of the entrepreneur.

It is worth noting that credit scoring is not meant to validate the repayment capacity of the borrower. Loan officers need to make sure that the loan applicant has the capacity to repay the loan. Credit scoring will predict if the borrower will maintain the repayment capacity based on the experience demonstrated by past borrowers with similar profiles of the credit risks.

Characteristics should be quantitative, but qualitative characteristics can be also used effectively in credit scoring. Trustworthiness of the applicant, if judged by the loan officer on a scale ranging from 'not trustworthy' to 'completely trustworthy', with some intermediate points, can have a strong association with the credit risk of the applicant.

Business-demographic characteristics

Business-demographic characteristics refer to the details of the business that will benefit from the loan, with its revenues used to repay the loan. In this context, real information should take precedence over formal data. For instance, if a business has been operating for ten years but was only officially registered a year ago, the business's age is considered to be ten years, not one. However, the fact that the business has only been formally registered for one year is likely important when assessing the credit risk of a loan taken to support this business.

The location of the business premises is another key characteristic for credit scoring, especially if the business operates in sectors like commerce or provides services to the general public.

Consolidated financial information

Consolidated financial information refers to the characteristics that measure various financial ratios, where the income of both the household and the business are combined, and liabilities are aggregated. When calculated accurately, these financial ratios can predict the likelihood of default for small, medium, and large businesses.

Compared to self-employed individuals, who represent the smallest and presumably most homogeneous entrepreneurial group, businesses vary significantly in many characteristics. The size of the business is likely the most important factor that contributes to this heterogeneity. Financial ratios allow for the measurement and comparison of business indicators across enterprises of different sizes on the same scale.

Loan transaction characteristics

Different loan products, even when targeting the same population, may attract applicants with varying risk profiles. For instance, in developing countries, loans in hard currencies typically carry lower interest rates, but they tend to be riskier for borrowers whose revenues are in local currency due to exchange rate risk. Microentrepreneurs seldom have income in hard currencies, even though they might prefer to operate in US dollars, British pounds, or euros, which are seen as more stable currencies. Consequently, the currency of the loan affects the credit risk.

Loan maturity is another risk factor: longer loans are generally riskier. However, offering a shorter loan with higher instalments, rather than reducing the requested loan amount, can be risky if the instalments exceed the borrower's repayment capacity.

The higher the interest rate, the greater the probability that the borrower will encounter difficulties in repaying the loan, as the interest increases the financial burden. However, credit institutions typically require riskier borrowers to pay higher interest rates to compensate for the higher credit risk. For this reason, risk-based pricing is an appealing concept, particularly for institutions dealing with clients who present a wide range of credit risks. This is true for microfinance institutions and SME lenders, which often lack effective credit scoring but

implement risk-based pricing strategies by offering interest rate discounts to borrowers with good repayment histories on their initial loans. A drawback of this approach, however, is that these institutions may need to offer relatively higher interest rates to all first-time borrowers, regardless of whether they are riskier or less risky. These higher interest rates can discourage many low-risk borrowers from applying for a loan, leading to adverse selection. This adverse selection problem can be exacerbated if the institution fails to provide timely interest rate discounts to good borrowers, encouraging them to seek better terms elsewhere. Opportunistic lenders may target these good borrowers once they demonstrate stable repayment behaviour, as they can offer competitive rates by avoiding high-risk clients and the associated costs.

Past credit behaviour

Credit history – also referred to as past credit behaviour – is typically the most predictive category of characteristics when assessing credit risk. While recent credit behaviour is more relevant for predicting future repayment patterns, the length of the credit history is also important. The longer a borrower has been exposed to credit transactions, the better, unless the credit history contains records of severe delinquencies. Characteristics such as the number of repaid loans in the last three years, the number of delinquencies over the past five years, and the highest delinquency recorded in the last five years are all key indicators of a borrower's credit history.

Credit institutions usually create their own credit histories for borrowers. However, credit bureaus and certain regulatory frameworks focus on collecting and consolidating credit histories from various financial institutions, as well as other businesses that extend credit, such as mobile phone operators and utilities. These consolidated credit files are then made available to financial institutions authorised to request and review a subject's credit history.

Credit reporting – the practice of credit institutions collecting credit histories, reporting these histories regularly and in a consolidated manner to an authority, which then systematises and provides them to credit institutions upon request – is an innovation that has helped advance financial inclusion in many countries where it is taken seriously. Various credit reporting mechanisms exist: some only report negative credit behaviour, while others report both positive and negative behaviour. The primary goal is to reduce information asymmetry in the credit market and enable sustainable financing for personal and business needs.

2.8.5 Statistical multivariate analysis

Once the profiles of credit risks are collected, characteristics that can discriminate credit risk need to be identified, and their individual contributions to the overall credit risk must be determined. In this context, multivariate analysis plays a central role in credit scoring. Statistical techniques offer various empirical methods that focus, in one way or another, on isolating the effect of each characteristic on credit risk, and then assembling relevant characteristics into a scorecard or neural network, which forms the foundation of each credit scoring algorithm. The statistical determination of each characteristic's contribution to overall credit risk is a key advantage of credit scoring over the judgmental and intuitive reasoning typically used by loan officers and credit rating tools.

Although humans are good at spotting patterns, including those associated with bad credit behaviour, when presented with numerous relevant cases, humans struggle to simultaneously process multiple characteristics that determine these patterns. For example, if a loan officer identifies two risk factors among the borrowers she monitors, by counting the prevalence of each factor, she may deduce the effect of each on the borrower's credit risk. However, such logic can induce bias because the joint effect of the factors needs to be calculated and considered. Human biases can affect decision-making when estimating the credit risk of a potential loan. If these biases make the loan officer more risk-averse, the financial institution may lose business. On the other hand, if the biases make the loan officer more risk-tolerant, the institution may face the financial consequences of underestimating credit risk.

2.8.6 The algorithm

The credit scoring algorithm tells the user, human or machine, how to proceed to estimate the classification of the credit risks (foreseen loan transactions) as good or bad credit risks. The accuracy of the estimation, with some margin, is known. The algorithm includes the precise rules for issuing a recommendation to accept, reject, or conduct a more thorough analysis of the credit risk. The lender can rely fully on such recommendations and proceed as recommended or allow loan officers and eventual credit committees question the recommendation of the algorithm.

Previously identified risk factors – characteristics of the credit risks which have credit risk discrimination power – can be arranged in a parametric way, forming a scorecard, or in a non-parametric way such as a decision tree. Nevertheless, the chances of a credit risk, which is scored by the algorithm, of becoming a bad credit risk, if approved, is known. This probability of a potential credit transaction becoming a bad credit risk is usually not enough for issuing a recommendation if to approve the transaction. The probability needs to be corroborated with the underlying economic calculations, which consider misclassification costs, but also the objectives of the credit institution. Some institutions want to grow at a faster pace, anticipating probably that the returns to scale will worth the increase in credit risk. In this case, the credit institution will be interested in gradually increasing the threshold of the acceptable bad credit risk probability – credit risks with higher probability of becoming bad will be accepted. If credit risk is already a problem for the credit institution, the threshold of the acceptable bad credit risk probability might be lowered.

All such rules need to be included in the credit scoring algorithm to ensure uniformity in the process of taking credit decisions and in the process of monitoring the performance of the credit scoring algorithm with respect to its credit risk discrimination power.

The credit scoring algorithm includes necessarily the characteristics of the loan application that have credit risk discrimination power, be these organised in a scorecard, a decision tree, a neural network or any other formula. The credit scoring algorithm needs to include the set of rules that guides the decision process once the formula issued a result – the output of the formula after being provided with an input. In most of the cases the output is a score, which can be assigned a probability of bad credit behaviour or the probability without a score.

2.8.7 Ethics

The use of credit scoring may raise legal concerns and these can determine how a credit institution uses own data for the purpose of pursuing own business goals. Ethical concerns have determined many countries, including the USA, which pioneered this movement, to restrict by law the use in credit scoring algorithms of certain characteristics deemed discriminatory.

Other issues from the ethical realm that might lead to legal restrictions could stem from the fact that credit scoring predicts the future. We say that past credit behaviour can predict future credit

behaviour, but this also concerns the current credit behaviour of borrowers which already influences the degree to which these will have access to credit in the future. Many countries restrict by law the duration for which a bad credit record can be stored with a credit bureau. They apply similar principles as in the right to be forgotten, where the regulator wants to give people and businesses the right to continue borrowing without being ‘stigmatised’ because of some bad credit behaviour demonstrated in the past. Regulators might impose a historic timeframe that should not be exceeded when collecting data for credit scoring purposes.

2.9 Differences in the conceptual framework of poverty scoring

By conducting a thorough literature review and leveraging our own professional experience, this thesis tried above to present the conceptual framework of credit scoring with all its complexities and nuances. Poverty scoring, from this perspective seems to have a much simpler conceptual framework, but this might be simply conditioned by the limited use of the technique. Although the literature on poverty scoring is very scarce, knowing that poverty scoring was inspired by credit scoring, we can sketch its conceptual framework.

The conceptual framework of poverty scoring is distinct from the conceptual framework of credit scoring in scope, definition of ‘bad’ cases and the profile of the scored subjects.

2.9.1 The scope of poverty scoring

The scope of poverty scoring is to classify subjects, usually microloan applicants, into poor and non-poor subject. Since information about subjects’ income is not reliable and expensive to produce, poverty scoring estimates the state of poverty of subjects through other reliable, easily observable, and relatively permanent characteristics of the subject. The subject can be the person applying for a loan or the entire household which shares the same poverty status as the head of the household.

2.9.2 Definition of bad cases in poverty scoring

Where the conceptual framework of credit scoring refers to bad credit risk, the conceptual framework of poverty scoring refers to non-poor subjects. The purpose of poverty scoring in microlending is not necessarily to screen out wealthier applicants, but to record their poverty

status. Screening out non-poor applicants is also a valid purpose of poverty scoring when organisations distribute welfare benefits. These aspects are described in detail in Chapter 5.

The definition of non-poor subjects depends on the definition of poor subjects first. As it has been argued in this thesis, being in a state of poverty means having no or little material possessions and lacking the income to procure them. A non-poor subject thus has many material possessions or has the income required to procure the needed material possessions or the basic services the material possessions offer. Since income is strongly associated with the value of material possessions, income is commonly used alone in determining if a subject is in a state of poverty or not, ignoring the material possessions of the subject. If the income of the subject is below a threshold, the subject is considered poor. Non-poor subjects thus have incomes above the threshold. The problem with the income is that it needs to be estimated because it is most of the time informal, irregular and the subject can manipulate the figures, depending on the context.

2.9.3 The profile of subjects to be assessed with poverty scoring

The profile of subjects which is collected for poverty scoring purposes differs from the profile collected for credit scoring purposes. In fact, only income characteristics and those associated with income would be required for poverty scoring, but since income of most subjects requiring poverty scoring is informal and irregular, other categories of data are required. Sociodemographic characteristics have poverty discrimination power. A rural household composed of young parents and many children have more chances of experiencing poverty than a peri-urban household with middle-aged parents and one child. Many indicators of poverty, such as lack of sanitation facilities, use of wood stove for cooking, and lack of access to internet are generally characterised as sociodemographic indicators. Business-demographic indicators could be used for estimating the profits of the microenterprise which supports the household. However, the spirit of poverty scoring is to estimate the income of the subject by observing easily-collectable characteristics that are strongly associated with poverty.

2.10 Chapter conclusions

The literature review presented in this chapter shows that the outlines of the conceptual framework of credit scoring date back to the late 1930s in the USA. In the post-Great

Depression period, the practice of using judgmental rating systems based on the experience and intuition of loan officers was not uncommon. In this context Durand (1941) pioneered the use of statistical methods in identifying credit risk factors in consumer financing. His research erected the pillars of the framework of the credit scoring technique and opened the way for further research.

The resemblance between the debate described by Durand (1941) and current debates in microfinance reveals important findings for microfinance institutions. This literature review and the enclosed analysis of actions and reactions that led to the current framework of credit scoring provide many lessons for the microfinance sector.

In 1958, FICO registered the sale of the first ‘credit scoring system’. Currently, ninety of the one hundred largest financial institutions in the USA and two-thirds of the largest one hundred banks in the world use FICO’s products (Fair Isaac Corporation, 2012). Nevertheless, the commercial success of FICO did not benefit the academic literature until recent publications (Oliver and Wells, 2001; Hand and Kelly, 2002; Zhu *et al.*, 2002) brought to light the results of its best practices and research findings.

Today, credit scoring is not in widespread use in microfinance, just as it was not in extensive use in the USA in the early 1960s, although the traits of the conceptual framework of modern consumer credit scoring were established and publicly available by 1964. With the expansion of the technique in consumer lending, Altman (1968) was the first to extend the use of credit scoring to corporate financing.

The Consumer Credit Protection Act of 1968 added legitimacy to credit scoring in the USA, which by the beginning of the 1970s had become a recognised industry. The Equal Credit Opportunity Act of 1974 marked a new stage in the history of the conceptual framework of credit scoring by prohibiting discrimination in credit granting practices on the basis of identities such as ethnicity and gender. Incorporation of such attributes in credit scoring algorithms was forbidden. To the extent that these factors were statistically significant, their exclusion reduced the accuracy of credit risk estimation, unless new risk factors could either compensate the lost accuracy or act as proxies for outlawed factors.

Along with the dynamic expansion of credit scoring in consumer lending, small business financing appeared as the next credit segment with potential for the diffusion of the technique. However, fears that commercial lending was not as homogeneous as consumer credit kept academics and practitioners away. It was only in 1995 that FICO (in partnership with Robert Morris Associates) started to offer pooled data credit scoring for small businesses.

By the end of the 20th century in the developed world the credit scoring technique was commonly used in granting consumer and small business credit. Simultaneously academics and practitioners started looking for credit risk evaluation techniques for developing countries. The work of Viganò (1993), proposing the application of credit scoring for evaluating small and micro firms in Burkina Faso, was a pioneering development in the literature. The publication of Schreiner (2010) is most significant in extending the use of credit scoring to microfinance.

The consolidated conceptual framework of the credit scoring technique, which has been developed on the basis of this critical review of literature, can be applied to personal, retail, mortgage, micro, small, medium, corporate, and other loan markets, new or old. This framework can enable both practitioners and academics to address their different approaches to the subject of credit scoring, especially the subject of the application of the credit scoring technique in microfinance.

The conceptual framework of credit scoring that is depicted in this chapter, but also the brief description how it was used in the design of poverty scoring, help in understanding what microfinance institutions expect from using credit scoring and poverty scoring separately and jointly.

Chapter 3 Methodology

Microfinance institutions are at the forefront of financial inclusion for low-income entrepreneurs. To grow and expand their services among low-income populations, MFIs must remain self-sustainable while staying focused on their target clientele. However, enforcing these practices can be challenging, especially when loan officers and other personnel involved in loan approval decisions do not have the appropriate tools to estimate credit risk and often equate wealth with creditworthiness.

In the absence of MFIs and similar institutions aimed at providing affordable financing to low-income entrepreneurs, these entrepreneurs have little to no access to finance. Relatives and friends can rarely help, considering that most also experience a certain degree of poverty, similar to the entrepreneurs themselves. The ‘loan-shark evil’, as discussed in previous chapters, can only represent a viable financing alternative in extreme cases. Financing business growth from own profits or revenues from other household members is challenging because of the high competition for funds needed for daily living, emergency savings, and long-desired household improvements.

The demand for microfinance among entrepreneurs is high. When presented with an opportunity to purchase equipment at a good price or buy supplies in bulk at a discount, a microloan, if provided in full, on time, and with a complete understanding of lending conditions, enables the business to grow. In microfinance, supply is typically the issue. Uncertainty is likely the main barrier for profit-seeking MFIs, while non-profit organisations struggle with sustainability if they receive limited donor funding.

This research assumes that the supply of microcredit is the primary issue and key lever in the provision of financial inclusion. MFIs play a crucial role in providing credit to financially excluded entrepreneurs who have the potential to lift themselves out of poverty if most of the barriers to entrepreneurship, of which access to finance is the most prominent, are lifted.

The joint use of credit scoring and poverty scoring should help for-profit and non-profit MFIs remain sustainable and committed to the social mission of microfinance.

3.1 Introduction

In Section 1.6, we elaborate on some theoretical constructs when discussing mission drift in MFIs. These constructs, based on the joint use of credit scoring and poverty scoring, should allow MFIs to stay both committed to the social mission and self-sustainable. MFIs, with or without external subsidies, should be able to cross-subsidise certain clusters of borrowers whose financial inclusion is of prime societal interest. The aim of the thesis was to answer these questions:

- Are poverty and credit risk correlated, and if so, how strongly?
- What do MFIs that use credit scoring have in common?
- What do MFIs that use poverty scoring have in common?
- Finally, what do MFIs that use both poverty scoring and credit scoring have in common, and how does this combined approach affect their profitability and outreach to poorer borrowers?

To address these questions, a mixed-method approach with a major focus on quantitative analysis was adopted. The dimension of the qualitative approach was not the usual one of interviews and focus group discussions but instead to lay down the background for the quantitative approach. This background consisted of a substantive study of secondary research sources of journal articles and books on the subject. This research dimension involved a critical examination of the theoretical, historical, empirical, and policy dimensions of the microfinance perspective on financial inclusion and poverty reduction. This qualitative dimension of the research has been reported in the previous chapter on the literature review and is resorted to in the later chapters too where relevant. The major gain from this engagement with the literature was to highlight the need for in-depth quantitative research to answer the questions we set before ourselves for this research project.

The quantitative research was conducted at two levels: the MFI level, where the unit of analysis is the MFI itself, and the client level, where the unit of analysis is the micro-borrower. MFI-level data can answer questions about the commonalities among MFIs that use poverty scoring, credit scoring, or both. Client-level data provide insights into the profiles of MFI borrowers, enabling us to observe how credit risk and poverty correlate and how this correlation affects outreach to poorer clients.

3.2 MFI-level data

The author initiated the collection of MFI-level data as part of the research activities under the Banque Populaire Chair in Microfinance at Burgundy School of Business, France. This initiative was closely tied to the MIX Market (World Bank Group, 2024b) – a growing database that provided MFI-level data from various developing countries. The MIX Market collected and disseminated dozens of business and financial indicators for MFIs that voluntarily submitted their data on an annual and often quarterly basis. These data include key figures from profit and loss statements and balance sheets, alongside essential business metrics for each MFI, such as the number of borrowers, branches, and loan officers.

The financial data, converted and disseminated in US dollars, and key business indicators proved invaluable in offering insights into the global microfinance industry. The initiative, which began in 1999, reached its peak outreach around 2014 but was discontinued in 2019. Previously, these data were accessible for free on an individual MFI basis, although accessing the entire collection came at a cost. In 2020, the entire dataset was incorporated into the World Bank’s Data Catalogue, making it freely accessible.

However, the database did not include information on the use of credit scoring by MFIs. To address this gap, a survey was created and sent to representatives of MFIs responsible for submitting data to the MIX Market. These contact details were listed on each MFI’s dedicated webpage on the MIX Market Internet portal, which was closed in 2019.

3.2.1 The credit scoring survey

The survey was sent to MFIs at regular intervals over several years (2012 to 2016), including to new MFIs that were joining the MIX Market data collection initiative. The goal was to gather as much information as possible about the use of credit scoring in these institutions.

The survey consisted of six questions. The first question required an answer. If the answer to the first question was ‘yes’, Questions 2 and 3 required an answer. If the answer to the first question was other than ‘yes’, Question 4 required an answer.

The last two questions – Question 5 and Question 6 – were optional. In fact, the entire survey was optional – MFI representatives could choose to ignore the emails requesting them to either

complete the questionnaire or forward it to the manager responsible for credit risk management within the MFI.

The six questions were:

Question 1: Is the MFI which you are representing using credit scoring?

Possible answers:

- Yes.
- No, but we intend to implement credit scoring within one year.
- No, but we intend to implement credit scoring within two years.
- No, but we intend to implement credit scoring within three years or later.
- No, we do not use credit scoring and do not intend to implement it.

Question 2: What definition describes best the credit scoring tool that the MFI which you are representing is using?

Possible answers:

- The scorecard was developed using a sample of past good borrowers and past bad borrowers, and statistical or mathematical procedures were used to determine the scores (weights) of selected factors.
- The scorecard was acquired as it is from another institution or consulting company.
- We do not calculate a credit score. We buy the credit score from a credit bureau.
- The scorecard was developed during meetings with own and, or invited credit experts who jointly agreed on the factors to be introduced in the scorecard and which score (weight) should be assigned to each factor in the scorecard.
- I do not know.
- None of the above (please provide your definition).

Question 3: If the MFI uses credit scoring, in which year and which month of that year credit scoring was fully implemented?

Possible answers: two integer numbers, a four-digit number for the year and a two-digit number for the month.

Question 4: If the MFI does not use credit scoring, why does it not use it?

Possible answers:

- We are implementing credit scoring now.
- We trust more the decision of our loan officers.

- We think that economic advantages of credit scoring are below the costs.
- We do not know the principles of credit scoring.
- We cannot find the required budget for the credit scoring implementation.
- The MFI had a bad experience with credit scoring.
- None of the above (please provide your definition).

Question 5 (optional): What is the name of the MFI you are representing?

Question 6 (optional): In which country operates the MFI you are representing?

Because some MFI groups submitted MIX Market data centrally through a single representative for all the MFIs in the group, it was important to identify which specific MFI the volunteered credit scoring information belonged to.

The initial survey was in English, but was subsequently translated into French, Russian, and Spanish to increase the chances of a valid reply. The French, Russian, and Spanish versions of the survey, together with the standard English version, were sent to MFIs based in countries where these languages are commonly spoken.

Question 1 in the survey asked whether the MFI currently uses credit scoring. To ensure accuracy, Question 2 requested the respondent to define the credit scoring tool used in their respective MFI. Four definitions of credit scoring were provided in Question 2, along with an option to provide the respondent's own definition or select 'I do not know'. The 'do not know' option was included to discourage respondents from selecting a random answer when the respondent was not sure how credit scoring was implemented in the MFI.

One of the four provided definitions in Question 2 best describes the concept of credit scoring – the respective credit scoring tool, developed using a recent representative sample of good and bad credit transactions of the MFI, provides most accurate estimations of the credit risk. MFIs that selected this definition and stated that they use credit scoring are defined hereinafter as 'custom-made credit scorers' (variable CS-CustomMade = 1).

Two other definitions of credit scoring refer to algorithms constructed by either credit bureaus or consulting companies using samples of good and bad credit transactions, not necessarily

belonging to the MFI. Credit bureaus in many countries have access to databases of good and bad credit transactions issued by banks and MFIs. Using such data, they can develop and market credit scoring algorithms or sell on request the calculated individual credit score based on inputs provided by the soliciting credit institution. Specialised consulting companies can also develop scoring algorithms using available samples of good and bad loan transactions. Credit scoring algorithms based on general data usually have less credit risk prediction power than custom-made algorithms constructed using the historical data of MFIs and banks. Non-custom-made algorithms usually ignore institution-specific loan characteristics and specific business approaches which translate into specific loan products and specific clientele.

Hereinafter, users of both non-custom-made credit scoring algorithms and custom-made credit scorers are collectively referred to as ‘statistic users’ (variable CS-Statistic = 1).

The last of the four definitions of credit scoring proposed in Question 2 referred to a subjective credit rating tool. Rating algorithms are not derived empirically but are based on the subjective experience of credit experts and veteran loan officers. MFIs that selected this definition are not considered ‘credit scorers’ even if they stated that they use credit scoring. Such rating tools facilitate the implementation of standardised loan appraisal procedures, which are needed, especially in large MFIs, but they lack empirical analysis and, based on the developed conceptual framework, stay outside the credit scoring perimeter. Such MFIs were defined as ‘credit raters’.

Hereinafter, users of credit scoring algorithms, whether custom-made or not, and credit raters are collectively referred to as ‘credit scoring users’ (variable CS-User = 1). This category is necessary to compare how users of any credit risk estimation tool, whether empirical or subjective, differ from MFIs that do not use any rating or credit scoring tools.

The responses to the credit scoring questionnaire were published on the website of the Banque Populaire Chair in Microfinance at Burgundy School of Business, which has since been closed following the discontinuation of the Chair.

3.2.2 Time-validity of answers and matching with MIX Market data

In Question 3, if the MFI declared using a credit scoring tool, the questionnaire asked when the tool was implemented in the institution. This information was needed to link the adoption of credit scoring to the corresponding data reports the MFI submitted to the MIX Market. Similarly, Question 1 included a time component in the possible responses. This was necessary to connect the new information about the non-use of credit scoring with the corresponding data reports submitted by the same MFIs to the MIX Market.

For example, if an MFI responded to the survey in November 2014 and indicated that it had been using credit scoring since October 2013, we could confirm that credit scoring was in use in that MFI from October 2013 to November 2014, the month the survey answer was received. Additionally, it was assumed that an MFI currently using credit scoring would continue to do so for the next two years. Therefore, the validity of the ‘yes’ answer to Question 1 would be extended from October 2013 to November 2016, two years from November 2014.

If the MIX Market database contained records for this MFI, all data reports with reference dates between October 2013 and November 2016 were updated to indicate that the MFI used credit scoring during that period. For instance, if the MFI submitted to MIX Market financial and business indicators for the years ending on 31st December 2012, 2013, 2014, 2015, 2016, and 2017 – six records in total – only the records dated 31st December 2013, 2014, and 2015 were updated with the new variable ‘CS-User’, marked with a value of 1, indicating credit scoring usage. The records dated 31st December 2012, 2016, and 2017 were not impacted since the validity of the response to Question 1 started in October 2013 and ended in November 2016. In the MFI records of December 2012, 2016, and 2017, the new variable ‘CS-User’ has been left blank. It was not assigned a value of 0, which would indicate that credit scoring was not in use.

The first three answer options to Question 1, starting with ‘no’, have the time component embedded in the response: ‘No (we do not use credit scoring), but we intend to implement credit scoring within’: one year, two years, or three years or even later, respectively. The validity of these answers started two years before the date of the response and continued for:

- Half a year if the MFI stated that it intends to implement credit scoring in one year;
- One year if the MFI stated that it intends to implement credit scoring in two years; and

- Two years if the MFI stated that it intends to implement credit scoring in three years or longer.

The deliberate reduction in the validity of these ‘no’ answers was intended to increase the accuracy of the responses, as circumstances change over time.

The last answer option to Question 1, starting with ‘no’ – ‘No, we do not use credit scoring and do not intend to implement it’ – had its validity starting only 90 days before the date of the response and continued for two years. Since some respondent MFIs were disappointed in credit scoring, we could not assume that if the MFI was not using credit scoring on the date of the survey response, it had not used it several months before answering the survey.

In the case of ‘no’ answers to Question 1, based on the time-validity of the response, the MIX Market data were updated with the variable ‘CS-User’, to which the value 0 was assigned.

If an MFI provided multiple responses to the credit scoring survey, such as answers from both the head of the credit department and the head of the risk department, or if the responses from the same MFI to different iterations of the credit scoring survey overlapped in terms of their validity period, the response closest in time – whether before or after the reference date of the MIX Market data record – was selected.

The credit scoring questionnaire yielded 625 valid responses. These answers came from 549 MFIs located in 106 developing countries. Several respondents did not want to reveal the name of their MFI, so their answers could be used in descriptive statistics and qualitative interpretations but not in the quantitative analysis.

3.2.3 Core business and social outreach indicators of MFIs and additional data sources

Adding to the MIX Market database the information about the use of credit scoring (and credit rating) allowed to perform a quantitative analysis to observe statistical differences between the users and non-users of credit scoring, between credit scorers and credit raters, and also between users of empirical or expert-based credit risk assessment algorithms and non-users of algorithms. Differences observed between users (CS-User = 1) and non-users (CS-User = 0) of credit scoring and rating techniques could shed light on and fill the literature gap regarding the

possible effects of the use of credit risk estimation tools on the business and social indicators of MFIs.

The collection of World Development Indicators (World Bank Group, 2024c) was used when country-level data were required in the analysis. Since the MIX Market data included the country of each MFI and the date the MFI data were referenced, the specific indicator from the collection of World Development Indicators, if available, could be identified and added to the analysis database. If a set of MFI data has been submitted to the MIX Market with the reference date 31st December 2015 we would look for the 2015 GDP per capita level for the year 2015 in the World Development Indicators. If a set of MFI data has been included in the MIX Market database with the reference date 31st March 2016 we would still look for the 2015 GDP per capita in the World Development Indicators, since this indicator is more relevant than the 2016 GDP per capita.

The quantitative analysis presented in Chapter 4 is based on the data constructed by linking the credit scoring survey with MIX Market data (World Bank Group, 2024b), with the addition of indicators from World Development Indicators (World Bank Group, 2024c). Since regression analysis excludes records with missing variables, the real number of data points used in each regression analysis is indicated under ‘number of degrees of freedom’ in each relevant regression summary table.

3.2.4 Poverty-scoring database

The MIX Market initiative to collect MFIs’ financial performance indicators had a parallel initiative called the ‘social performance initiative’. In a similar way, MFIs throughout the world would submit, once a year, their social performance indicators. The initiative collected indicators on MFIs’ social goals, governance, HR policies and practices, products and services, client protection, and environment protection policies. The social goals section included the MFIs’ answers to the following questions:

Question 1: Does your institution measure the poverty levels of its clients?

Possible answers:

- ☐ Yes
- ☐ No
- ☐ Unknown

Question 2: Please indicate which tool(s) your institution uses to measure client poverty.

Possible answers:

- ☐ Grameen Progress out of Poverty Index
- ☐ IRIS / USAID Poverty Assessment Tool
- ☐ Per capita household income
- ☐ Per capita household expenditure
- ☐ Participatory wealth ranking
- ☐ Housing index
- ☐ Food security index
- ☐ Means test
- ☐ Own proxy poverty index
- ☐ None of the above

Question 3: Which development goals does your institution specifically pursue through its provision of financial and non-financial products and services? Please select a maximum of five.

Possible answers:

- ☐ Increased access to financial services
- ☐ Poverty reduction
- ☐ Employment generation
- ☐ Development of start-up enterprises
- ☐ Growth of existing businesses
- ☐ Improvement of adult education
- ☐ Youth opportunities
- ☐ Children's schooling
- ☐ Health improvement
- ☐ Gender equality and women's empowerment
- ☐ Water and sanitation
- ☐ Housing
- ☐ None of the above

From the above answers, the dummy variable 'PM-User' was created following these rules:

- All MFIs which declared to measure the poverty level of their clients have been assigned the value 1 to the variable ‘PM-User’, which has been created for this purpose [PM-User = 1];
- All MFIs which declared to not measure the poverty level of their clients have been assigned the value 0 [PM-User = 0]; and
- For MFIs which answered “Unknown” to Question 1, the variable has been left blank.

From the answers to Question 2, we could identify the poverty measurement techniques belonging to the poverty scoring family. The Grameen Progress out of Poverty Index (Innovations for Poverty Action, 2024) is based on poverty scoring. This initiative covered the largest developing countries. Poverty scorecards have been developed using country-wide poverty assessment questionnaires and have been offered for free to MFIs, public and private organisations involved in poverty alleviation programmes, and the public. Under the initiative, MFIs could receive generic, but often custom-made, help with understanding and implementing poverty scoring.

The IRIS / USAID Poverty Assessment Tool – probably a parallel initiative to the Progress out of Poverty Index described above – was driven by the IRIS Center at the University of Maryland, with the support of USAID and inputs from the Grameen Foundation. This technique to measure the poverty level of subjects and their households quickly and accurately is based on national household surveys that cover expenditure or income. The result, using statistical analysis, was country-specific poverty scorecards with 15-18 indicators that would benchmark a subject to a selected poverty line. Such poverty assessment tools have been built for the Philippines using the 2004 Annual Poverty Indicators Survey (USAID, 2010a), for the West Bank based on data from the 2007 Palestinian Central Bureau of Statistics’ Expenditure and Consumption Survey (USAID, 2010b), and for Liberia using a nationally representative household survey conducted in 2008 (USAID, 2011).

A new dummy variable, ‘PM-Scorer’, was created to indicate that an MFI uses poverty scoring. MFIs that in Question 2 selected either Grameen Progress out of Poverty Index or IRIS / USAID Poverty Assessment Tool as their poverty measurement tool are classified as ‘poverty scorers’, and the dummy ‘PM-Scorer’ has the value 1 in this case. The dummy ‘PM-Scorer’ has value 0 in all other cases where we know that the MFI measures the poverty level of its

clients (where PM-User = 1) but uses a technique which is not poverty scoring. Where we know that the MFI does not measure the poverty level of its clients (where PM-User = 0) or the respondent was unsure about poverty measurement in the surveyed MFI (where PM-User is blank), the variable 'PM-Scorer' was left blank.

The dummy 'PM-Rater' is the opposite of 'PM-Scorer'. It has the value 1 where the dummy 'PM-Scorer' has the value 0 and the value 0 where the dummy 'PM-Scorer' has the value 1.

Other poverty measurement techniques used in MFIs which are not from the family of poverty scoring are:

- Per capita household income: The technique is based on calculating total household income from all sources such as work, capital, and government transfers, cash and in-kind. The sum is divided by the number of members living in the household.
- Per capita household expenditure: This indicator is the sum of total household expenditure, including consumption and non-consumption items, divided by the number of members living in the household.
- Participatory wealth ranking: A novel approach to poverty measurement, the technique relies on poverty-defining criteria that respective communities propose themselves. This technique allows representatives of communities to define what constitutes poverty and rank concerned households according to proposed indicators from the poorest to the least poor.
- Housing index: The indicator is based on a scorecard with a few indicators describing the house, the number of rooms, the material used for building the house and presence of utilities such as running water and sewage. Since the scorecard is not derived through rigorous statistical techniques applied to data obtained from national poverty assessment surveys, such techniques, although simple and probably quite accurate, do not qualify as poverty scoring.
- Food security index: This indicator is based on a scorecard measuring the availability, stability, and access to food.
- Means test: The technique is based on a simplified household survey to determine poverty levels. A scorecard is derived and used to rank households.

- Own proxy poverty index: May refer to any other measurement that MFIs can use. Because the MFI did not identify the technique as being in the category of poverty scoring, it is assumed to be an alternative technique with less statistical accuracy.

The answers to Question 3 were reviewed, leading to the creation of the variable ‘# social goals’, which counts the number of non-financial social goals the MFIs declare to target. It is common for an MFI to have financial-related development goals. However, having non-financial development goals, such as improving adult education, children’s schooling, health, and access to water and sanitation, is extraordinary and requires additional effort without obvious financial returns. The answer required a maximum of five goals to be listed. If certain non-financial goals were selected, it was assumed that they were important for the MFI.

The four new variables ‘PM-User’, ‘PM-Scorer’, ‘PM-Rater’, and ‘# social goals’ enriched the social performance database of the MIX Market. To integrate MFIs’ financial performance data with social performance information, the two databases were merged. The merger was conducted at the MFI name level and the year of reporting.

The quantitative analysis in Chapter 5 is based on the data constructed by merging the MIX Market financial performance data with social performance data (World Bank Group, 2024b), supplemented by indicators from the World Development Indicators (World Bank Group, 2024c). Since regression analysis excludes records with missing variables, the real number of data points used in each regression analysis is indicated under ‘number of degrees of freedom’ in each relevant regression summary table.

3.2.5 The database capturing the joint use of poverty scoring and credit scoring

To be able to identify MFIs that use jointly poverty scoring and credit scoring, to the data constructed by merging MIX Market financial performance data with social performance data (World Bank Group, 2024b) the data of the credit scoring survey have been added. The quantitative analysis presented in Chapter 6 is based on these data. The real number of data points used in each regression analysis is indicated under ‘number of degrees of freedom’ in each relevant regression summary table.

3.2.6 Regression analysis

To identify commonalities among MFIs that use poverty scoring, credit scoring, or both, we employ regression analysis, a technique from the domain of multivariate statistical analysis. As with credit scoring and poverty scoring, where regression analysis is often used to isolate characteristics that contribute to a loan applicant being riskier or wealthier and to calculate the size of their contribution without interference from other characteristics, we aim to use regression analysis to determine the contribution of credit scoring, poverty scoring, and the combination of both techniques to the business and social indicators of MFIs.

In an ideal research setting, we would have a large number of MFIs randomly assigned to one of the four groups. Group one would implement credit scoring and use it consistently during loan approval, with the restriction that poverty scoring would not be used. Group two would use poverty scoring consistently to measure and correct social outreach indicators, aiming to increase or at least maintain the same share of borrowers at high risk of experiencing poverty, but would be forbidden from using credit scoring. Group three would use both poverty and credit scoring together, screening out risky borrowers while aiming to maintain the same share of borrowers with a high risk of experiencing poverty. The final group – group four – would serve as the control group, forbidden from using both credit scoring and poverty scoring. The social and business indicators of this last control group would be compared with those of the other groups after a certain period of time, deemed necessary for the use of credit scoring and poverty scoring to produce economic and social effects in the respective MFIs. Notable differences observed in any of the three groups that changed their lending practices could likely be attributed to the intervention, which is the implementation and use of one or both scoring techniques.

A less ideal, but still very interesting, research approach would be to find the same four groups of MFIs in the collected and compiled database spanning an important period of time. Group one MFIs would not have used either credit scoring or poverty scoring when they first appeared in the database but started using credit scoring alone soon after. Group two MFIs would also not have used either credit scoring or poverty scoring when they first appeared in the database but started using poverty scoring alone soon after. Group three MFIs would not have used either credit scoring or poverty scoring when they first appeared in the database but started

using both scoring techniques soon after. Finally, group four MFIs would not have used either credit scoring or poverty scoring when they first appeared in the database and would still not be using either technique by the end of the study period. Assuming that the retroactive distribution of MFIs into the four groups is not biased and no factor other than the use of credit scoring and poverty scoring influences the groups, a comparison of initial and final economic and social outcomes between the groups could yield viable results regarding the effects on MFIs of the individual and joint use of credit scoring and poverty scoring.

Time-series analysis was another explored research method. Knowing, for a larger set of MFIs, when each MFI started using credit scoring or poverty scoring during the analysis period, one could conduct time-series regression analysis to determine if the use of a scoring technique is associated with certain economic or social outcomes. For the available data to be relevant for time-series regression analysis, records must be collected at regular intervals, and only records of MFIs that changed their status as users of credit scoring and poverty scoring at some point between the start and end dates would qualify.

Simple regression analysis was the only viable research method for the available MFI-level data, as it did not require time consistency, which was impossible to ensure, given the voluntary nature of the survey responses. It also did not necessitate the initial or ex-post classification of MFIs into one of the four categories, as the low number of MFIs meeting the grouping requirements made this approach unfeasible. Regression analysis was therefore selected as the most straightforward method to identify and interpret the contribution of the created dummy variables, which measure the use of credit scoring and poverty scoring on the business and social outcomes of the MFIs, provided that the necessary assumptions for obtaining unbiased results were met.

3.3 Borrower-level data

Using MFI-level data, such as those produced following the steps described in the previous subchapter, it is possible to indirectly estimate whether poverty and credit risk are correlated. However, it is likely impossible to dynamically observe whether this correlation changes as the level of poverty of MFI clients increases or decreases. Without appropriate client-level data, we cannot determine whether ‘poor and safe (in terms of credit risk)’ borrowers exist.

A sample of approximately 800 real loans issued by a microfinance institution from the Eastern Mediterranean was used as the primary data for the quantitative analysis presented in Chapter 7. These loans were the first loans issued by the MFI to microentrepreneurs engaged in basic agricultural activities, most of whom were experiencing a certain degree of poverty. The anonymised data contained the characteristics required to assess the creditworthiness of the applicants, as well as the characteristics needed to calculate the poverty score. Repayment behaviour for these loans was available, from which the loan's status as either a good or bad credit risk could be determined. Logistic regression was used to create a credit scoring algorithm to estimate the probability of default for these loans. Logistic regression is suited for data in which the dependent variable – the credit risk class – is dichotomous (0 – good credit risk and 1 – bad credit risk), and where other independent variables can be either dichotomous or continuous. The credit score and probability of default were calculated for each loan.

For poverty scoring, the MFI used an existing poverty scorecard and accurately collected the required characteristics. With the characteristics and scorecard in hand, a poverty score was calculated for each borrower.

Poverty scores and credit scores were then correlated to calculate the direction and strength of their relationship. Borrowers were grouped into three categories based on decreasing poverty scores, and three separate correlation analyses were conducted for each category to observe whether the correlation coefficients maintained the same sign, strength, and statistical significance.

The robustness of the developed credit scoring algorithm could be tested, as the real classification of borrowers as good or bad credit risks was known. However, the robustness of the poverty scoring algorithm could not be tested because loan officers were primarily focused on estimating household revenues and tended to neglect household expenses. Households with more adult members generally had larger revenues, justifying larger loans. However, the estimated household expenses did not grow in proportion to the household size.

It is assumed that most of the information collected by loan officers, with the exception of revenues and expenses, for loan underwriting and poverty scoring was accurate. Loan officers were obliged to carefully collect underwriting information, knowing that their superiors could

check the quality of the data. However, this was probably not the case for the data used for poverty scoring. Nonetheless, it is unlikely that borrowers would systematically misreport poverty scoring data, as this would risk them being identified as providers of unreliable information. The advantage of poverty scoring is that it focuses on easily observable characteristics, which are also relatively stable over time, such as the number of dependants, education level, and availability of sanitation facilities. Misreporting one characteristic would not significantly alter the probability of a household experiencing poverty. In borderline cases, one untruthful answer could make a difference, but since the MFI did not reject loans based on the poverty score, it is assumed that neither the borrowers nor the loan officers had an incentive to report or collect untruthful data for poverty scoring.

3.4 Chapter conclusions

Microfinance institutions play a crucial role in the financial inclusion of poor entrepreneurs. However, balancing economic sustainability with a social mission can be challenging, particularly when personnel equate wealth to creditworthiness. This chapter outlines the methodology used to create the theoretical constructs and empirically test their viability in this study. This study adopted a mixed-methods approach, with a major focus on the quantitative approach, which aimed to identify common traits among MFIs using credit scoring, poverty scoring, and assessing the impact of using both scoring techniques on MFIs' profitability and outreach. The quantitative approach was also used to explore the correlation between poverty and credit risk, assumed positive and strong in mainstream finance.

Data collection was conducted at two levels: MFI-level, where the MFI itself is the subject of study, and client-level, where MFI clients – entrepreneurs experiencing varying degrees of poverty and borrowing microloans to sustain and grow their activities – are the subjects of quantitative analysis.

The collection of MFI-level data involved leveraging the MIX Market databases, which contained financial and social performance data at the MFI level, as well as a custom survey targeting the same MFIs, with questions regarding the credit scoring practices used within them. The credit scoring survey consisted of six questions that asked MFIs about their use of credit scoring and the types of scoring tools they employed.

Client-level data comprised a sample of real loans issued by a microfinance institution to microentrepreneurs engaged in agriculture.

Quantitative analysis was primarily used to answer the research questions posed. Quantitative research offers several advantages over other types of research, particularly qualitative methods. Quantitative research relies on numerical data and statistical analysis, which minimises bias and ensures replicability. With representative samples, which we believe to have collected, quantitative research findings can be generalised to the entire studied market. Furthermore, quantitative research allows for complex statistical analysis, enabling the identification of patterns and correlations and isolating associations between variables that may not be apparent through qualitative methods. Quantitative research provides clear and definitive conclusions that can guide decision-making and policy formulation. All these advantages make quantitative research invaluable in fields requiring generalisation to entire populations and markets and in identifying statistical relationships between variables.

Chapter 4 The use of credit scoring in microfinance institutions

Access to affordable financial services tailored for the needs of populations with low revenues has the potential to improve the quality of people's lives and safeguard the sustainability of their small businesses (Armendàriz and Morduch, 2005; Yunus, 2003). On one hand technological progress allows a constant reduction in costs of providing saving and payment facilities to low-income households supporting a sustainable development of these services (Ashta, 2011), on the other hand, information asymmetry and uncertainty stand in the way of providing cheaper microinsurance and microcredit services. Longstanding credit institutions which lend to low-income populations are those that deal correctly with these problems or manage to rely on volatile subsidies. Such institutions face many risks, but credit risk is usually the most important (Centre for the Study of Financial Innovation, 2011, 2012; Khan and Ashta, 2013).

4.1 Introduction

Credit risk is inherent in every loan. It exists in any transaction in which money is received after the delivery of goods or services. When goods or services are paid for by cheque, credit risk is also present in the transaction, as it may only become apparent at the point of cashing the cheque whether there are insufficient funds to cover it. In this context, a chequebook acts as a form of credit, potentially providing some financial inclusion to poor entrepreneurs.

Transactions in which borrowed amounts, along with incurred interest and associated fees, are repaid on time according to the agreed schedules are considered good credit risks. 'Good' borrowers are those who engage in transactions that are deemed good credit risks. Conversely, transactions in which repayment is compromised or significantly disrupted are classified as bad credit risks, and by analogy, the respective borrowers are considered 'bad' borrowers. Section 2.8.3 describes the idea behind the definition of good and bad credit risks for credit scoring purposes. An overindebted, defaulting borrower with multiple loans may choose to repay the loan of one financial institution while defaulting on loans from other institutions. This would make the client appear as a good borrower to the fortunate institution and a bad borrower to the other lenders. The fortunate lender may become aware of the borrower's bad credit history if credit reporting is available and reliable or if the lender learns of it through the market. As a

result, the fortunate lender will not extend further credit despite having experienced no issues with the borrower. A reputation as a good borrower, as certified by credit history or relevant people, is difficult to build but easy to lose. For poor borrowers, this reputation can serve as an asset against which new loans may be extended. As it takes time to build a ‘good borrower’ reputation by receiving and repaying loans, financial institutions must provide loans to new borrowers to expand their client base. Although new borrowers are generally more likely to default, even long-standing good borrowers can default due to unforeseen circumstances or overconfidence on both sides – the borrower and the lender – who may assume that because the borrower repaid past loans on time, a new, usually larger loan will also be repaid.

In the absence of subsidised loan guarantee schemes, good borrowers indirectly pay for the losses that bad borrowers cause to lending institutions. Even when a lending organisation uses an effective risk-based pricing mechanism, and all borrowers pay interest rates which are individually adjusted to the estimated credit risk, those borrowers who did not default but paid a credit risk premium indirectly contributed to the compensation of a part of the losses generated by the borrowers who defaulted. A fundamental component of the business model of credit issuing companies, including the MFIs, is the ability to determine with a certain degree of accuracy the creditworthiness of loan applicants and the debt burden these applicants can safely handle. Most not creditworthy applicants do not receive credit when they apply, but some manage to borrow. An important share of creditworthy loan applicants receives loans. Most of these loans are repaid on time or with insignificant delinquency. Some of these loans register more significant delinquencies but manage to recover or reschedule the loan to avoid default. Some creditworthy borrowers default on their debts due to unforeseen circumstances or excessive debt burden, becoming bad borrowers. In such circumstances, what has been assessed as a potential good credit risk reveals to be a bad credit risk. As long as bad credit risks do not outweigh financially the good credit risks, the financial institution remains afloat.

In the context of microfinance, this credit risk sharing at the cost of the good borrower has certain benefits for society. For example, poorer risky entrepreneurs who have little to lose in the case of default can receive loans to test their business ideas and potentially develop a sustainable enterprise or, at least, gain valuable experience. Risk sharing has also important limitations. Compensation of bad borrowers’ losses through rising interest rates can lead to an exodus of good borrowers, undermining the financial viability of the credit institution. Because

good borrowers do not apply for expensive credit, the share of bad borrowers who do apply increases. This leads to an increase in the proportion of bad borrowers who apply for loans and, often, a higher number of bad borrowers who get loans. The increasing losses caused by bad credit risks can even lead to the collapse of a financial institution. The bankruptcy of an MFI generates negative externalities determined by the additional costs inflicted on society due to the disappearance of basic financial services for the persons who need them the most. The loss of jobs and additional revenues the MFI was generating in the poor communities through renting space for branches and offices, and through payment of services such as the provision of drinking water and other supplies, represents additional negative externalities.

In all credit segments, this adverse selection – the unintended selection of riskier borrowers who are attracted by relatively higher interest rates than those considered acceptable by safe borrowers – is difficult to overcome because of the asymmetry of information between loan applicants and financial institutions. In microfinance, one part of the future loan transaction – the applicant – does not necessarily have more or better information than the other part – the lender. The applicant can be ignorant about her repayment capacities but applies for a loan because other neighbours did apply. Since institutional efforts directed at knowing better the repayment capacity of potential clients involve a cost which increases with the level of informality in the economy, the use of the tool of credit scoring should be an efficient technique to decrease adverse selection.

In this chapter, we empirically test the effects of credit scoring on the outreach indicators of microfinance institutions. We expect to see an increase in the number of borrowers and loans. If loan officers can confidently rely on credit scoring, they should be able to make more and better credit decisions, resulting in more borrowers and more loans per loan officer. An MFI may not necessarily have a better portfolio in terms of credit risk, but as long as the risk remains within acceptable limits owing to credit scoring, the MFI will be interested in expanding its portfolio and client base.

4.2 Two lending approaches

Microfinance institutions that practice individual lending face information asymmetry more intensely than those MFIs that practice group lending. In group lending, borrowers use the inside information they have on other borrowers of the same group to ensure that the group

loan has a high chance of repayment. Microfinance institutions that practice individual lending also face information asymmetry more intensely than traditional financial institutions because micro-borrowers, who are generally poor and illiterate, provide inadequate quality and quantity of documentation to prove creditworthiness. MFIs that practice individual lending deal with this problem by adopting one of the two mainstream banking approaches to allow lending with a certain level of confidence. One approach is relational and qualitative, whereas the other is transactional and quantitative. Both approaches are extremes of the trade-off between control and per-transaction profit that financial institutions set (Rajan, 1992). Both approaches can be used simultaneously by strategically allocating the capacity of the lending institution across relationship and transactional lending (Boot and Thakor, 2000).

In microfinance, the first tactic – relational-qualitative – requires that the loan officer establishes a relationship with the credit applicant and her professional and personal entourage. As the loan officer gains trust in the client and the information asymmetry between the lender and the borrower reduces, the micro-borrower receives larger loans, which gradually level up to the amounts needed to cover working capital needs but also to realise investments. Berger and Udell (1995) showed that in the USA, small firms with longer banking relationships are less likely to pledge collateral than other small firms. Low-income entrepreneurs chronically lack acceptable collateral.

This approach, which is quite effective in new microcredit markets, remains expensive because of the high costs of initial credit transactions. The MFI usually reaches sustainability in financing a client after several cycles of insufficient and ‘subsidised’ credit, if only the already confirmed good borrower is not poached, alone or together with the loan officer, by an opportunistic competitor, which could be an MFI or a bank.

Borrowers expect a significant reduction in the interest rate with each new loan from relational lenders, but the financial institution cannot always afford to offer such rewards as it needs to recover the initial investment and start making profits by serving the account. If the financial institution does not decrease the risk premium fast enough, the borrower is more likely to establish a relationship with another financial institution (Greenbaum *et al.*, 1989), which is likely to be a transactional lender. The advent of credit bureaus, which also gather information from microfinance institutions, facilitates customer churn. Clients who can prove good past

credit behaviour can choose a cheaper lender that does not invest in the relationship with their clients, as relational lenders do.

The second, quantitative-transactional tactic, generally involves the use of credit scoring or an expert technique. In markets with fast and effective means to enforce loan contracts, the need for tools with high credit risk discrimination power is less pronounced or critical. In this chapter, we explore the effects the use of credit scoring has on the outreach indicators of the MFIs, assuming that MFIs which already invested in credit scoring or expert scoring techniques allocate strategically their capacity principally towards transactional lending.

4.3 Credit risk under the microscope

Credit risk originates from both the ability of the borrower to repay the loan when it is due and the willingness to repay the loan. At the time of loan appraisal and eventual approval, a borrower's future reimbursement capacity is uncertain. It depends on future incomes to be cashed in, including the gains from the investments made with the credit funds, and expenditures to be paid in the future, to which should be added the incurred interest and eventual loan-related fees. The borrower has also to repay gradually the loan. Future incomes and expenditures of small businesses in developing countries can be affected by many hazards, such as market, legal, and political risks, and entrepreneurs' personal problems, such as health issues (Jacoby and Skoufias, 1997; Hazarika and Sarangi, 2008). In many developing countries, borrowers prefer to borrow in euros, British pounds, and US dollars, as the interest rates for hard currencies are generally lower. MFIs which receive donor funding, cheap loans from DFIs, or borrow on international markets, generally receive hard currency which is often on-lent to borrowers in the same currency to avoid conversion fees and currency exchange risks. Entrepreneurs who borrow hard currencies generally operate in local currency. In addition to the fees and interest borrowers pay when they borrow foreign currency, they also bear the exchange risk.

The analysis of past and current revenues and expenditures of the loan applicant allows the loan officer to estimate the applicant's future repayment capacity under certain scenarios. Unfortunately, the predicted satisfactory repayment capacity is not relevant if the borrower does not want to repay the loan or if circumstances suddenly deteriorate the borrower's financial sustainability. The added value of projections based on repayment analysis is also

reduced by applicants' overly optimistic business expectations and false evidence of repayment capacity, which are easy to fabricate in the informal or semi-formal environment in which most microentrepreneurs operate.

Willingness to repay a loan depends on the personality of the borrower and expected consequences of default. Loan officers are usually unfamiliar with personality assessment techniques. However, they subjectively measure the applicant, showing empathy and using intuition to deduce the applicant's future actions. Such behavioural analysis of micro-borrowers boils down to answering the question whether the loan applicant can be trusted if she seems creditworthy. Establishment of business plans with forecasted cash flows and balance sheets seems to have reduced utility in microfinance. However, it could be that the loan officer's time spent with the applicant and dealing with applicant's documentation when making the repayment forecasts helps the loan officer discover the applicant as well as her business and make an objective credit decision covering the current ability to repay the loan and current willingness to stay committed to repay the loan.

Microfinance has the advantage of short, frequent loan cycles. A loan officer usually manages a portfolio composed of loans of several dozen or even hundreds of active borrowers. Even if the institution has low repayment delinquency levels, each loan officer is constantly confronted with missed payments and clients who struggle with repayments until they default. From several iterations involving bad borrowers, most loan officers infer, accurately or not, certain traits shared by bad credit risks and in consequence by bad borrowers. It could be that loan officer's time spent in quantitative analysis of the potential borrower is in fact a qualitative assessment of the applicant focused on those traits which the loan officer associates with bad credit behaviour.

Credit scoring does not have the disadvantage of the long and subjective analysis of the loan officer. Underlying algorithms are based on empirically identified characteristics and combinations of characteristics specific to bad credit risks and good credit risks. Credit scoring is largely used in developed countries in consumer credit and other large and homogeneous credit segments, but also, we believe, in low-income credit segments to estimate with reasonable accuracy the credit risk of the prospected loan at lower cost. Obviously, the set of available characteristics for scoring is limited to: the ones previously captured by the loan

application form; a few characteristics that can be generated by the lender using data on previous credit behaviour of the applicant – repayment of past loans with the lender; and information procured from credit bureaus and similar registries.

In addition to quantitative data (requested loan amount, income, turnover), the computerised loan application form can capture relevant qualitative indicators in form of dichotomous (male / female) and ordinal (poor / good / excellent business skills) variables. Unfortunately, a computerised loan application form will badly convey to the credit decision body the bad feeling about the potential borrower – an emotion that a loan officer can easily express at any time during loan appraisal or in the credit committee, when the loan officer will meet with colleagues from risk department and own supervisors to decide the loan approval.

To summarise, credit scoring is meant to help credit institutions manage the credit risk. A lender can use it to reduce its credit risk exposure – stricter cut-off scores will ensure that only low credit risk transactions are approved. The institution can also use the credit scoring tool to increase outreach: by fixing a more permissive risk threshold and automating, to the extent possible, the decision process, it approves more credit transactions but maintains the overall credit risk exposure within a certain limit.

In microfinance, borrowed and repaid amounts are small, forcing the MFIs to bet on the volume of transactions. Bigger numbers of borrowers and bigger numbers of loans are generally considered good for the society, because financial services are offered to more people needing them. The scale effect usually makes these services cheaper. The use of credit scoring should help MFIs grow, while controlling the credit risk exposure and over-indebtedness.

4.4 Correlations as indicators for hypothesis development

Initial analysis of correlations between key MFI indicators and MFIs' status as credit scoring or credit rating users indicates on potential research paths to follow to test the hypothesis that the use of credit scoring in MFIs is associated, all other things being equal, with more borrowers and more loans and, or better control of the credit risk.

For correlation, but also further statistical analysis, from the database have been removed the MFIs that practice group lending. All datapoints in which individual borrowers represent less than 97 percent have been removed. Group lending, as described in the introductory chapters,

represents the innovation that brought microfinance on the agenda of international organisations working on combatting poverty. In developing countries, poor people from communities in urban neighbourhoods and villages, could organise themselves in self-help groups for the purpose of borrowing and getting access to other financial and non-financial services. Acting as one borrowing entity, a self-help group organises itself and when gets a loan, it manages its disbursement to creditworthy group members. The group organises collection of repayments, facilitates mutual help for timely repayments, and enforces the repayment obligations by applying social pressure. This and similar group lending techniques are not perfectly suitable for credit scoring algorithms designed to estimate the probability of default of individual borrowers. Suggestions of developing credit scoring algorithms for group lending, where group characteristics act as predictors of future repayment behaviour, or to use the credit score of group leaders as a proxy for the creditworthiness of the group have been proposed by researchers and practitioners, however, the nature and the scope of group lending are different from individual microcredit. Group lending targets the early entrepreneurial needs of poor, financially illiterate, and financially excluded people. Group lending can ensure outreach which grows in geometric progression, but it cannot deal with meeting the particular financial needs of growing microenterprises. Even the needs of self-employed people are seldom met by group lending because of small amounts given to members, short maturities but frequent (generally weekly) repayments, and time-consuming rituals meant to maintain group's cohesion rather than members' entrepreneurial self-interest.

From the correlation analysis have been excluded the MFIs that practice exclusively or predominantly lending to women. All datapoints in which the share of women borrowers was greater than 70 percent have been removed. In fact, many such datapoints have been removed when group lenders were removed. The self-help group model targets mostly women because they tend to get more comfort in dealing with financing in a group of peers. MFIs focussing on women tend to replicate some of the principles of group lending, which trade off individual needs of borrowers for better repayment incentives. The MFI might declare as all women borrowers are individual borrowers, however the self-help group structure is maintained for better repayment control.

From the sample were removed the MFIs with fewer than 10 employees and a couple of MFIs with more than 10,000 employees – outliers which were far apart from the estimated end of the

employee distribution at 3,500 employees. In the remaining group of credit scorers composed of 74 datapoints the minimum was 11 employees in the MFI and the maximum 3,476. In the group of non-credit scorers (includes the credit raters) composed of 233 datapoints the minimum was 10 employees in the MFI and the maximum was 2,833. In 8 additional datapoints it is known that the MFI uses a credit risk assessment tool, but the scoring or rating nature of the tool could not be identified.

In Table 5 we present the Pearson correlation coefficients between a selection of MFI characteristics and the MFIs' status as users of credit scoring. Correlation coefficients (abbreviated 'Coef.' in columns 2, 5 and 8), their two-tailed significance levels (abbreviated 'Sig.' in columns 3, 6 and 9) as well as the number of datapoints participating in the correlation calculation (abbreviated 'N' in columns 4, 7 and 10) are presented for MFIs that: use credit scoring ('Credit Scorer' in the head row); use a credit rating tool ('Credit Rater' in the head row); and use a scoring tool for credit risk estimation ('Scoring Tool' in the head row – includes the group of scorers, the group of raters and few datapoints which we could not accurately classify in one of the two groups). It is worth noting that we did not try to correct the self-declared status of the MFI as user of credit scoring, credit rating or none of the enumerated. We assumed that eventual random errors cancel out in a large sample of datapoints.

Since raters and scorers form the group of credit risk estimation tool users, the source of a significant correlation observed in the 'Scoring Tool' group can be traced to the group of raters or scorers or both. For easier interpretation of correlation coefficients, those which indicate a statistically significant correlation at 5 percent level are presented in bold, while those which are significant at 1 percent are also underlined. We can occasionally mention correlation coefficients significant at higher than the 5 percent threshold, say 9.8 percent – meaning a 9.8 percent chance that the observed correlation coefficient occurred by chance in the sample, however in the entire population of MFIs this correlation would be different.

Pearson correlation coefficients are used in statistics to measure the strength and direction of a linear relationship between two variables in which one can be binary, such as in our case when the status of the MFI as user of credit scoring can be either true (1) or false (0). If we do not know, or not sure about the status, the corresponding binary value is missing and correlation calculation skips that record. Coefficients range between -1 and +1. A Pearson coefficient of

- 1 indicates a perfect negative correlation, meaning that every time one variable decreased, the other necessarily increased. A Pearson coefficient of + 1 indicates a perfect positive correlation. In our binary cases this would mean that every time an MFI changes its status from non-user of credit scoring to user of credit scoring the other measured variable will necessarily increase. A correlation of 0 shows no relationship between the movement of the two variables. A negative or positive correlation coefficient which is close to 0 indicates a weak correlation, negative or positive respectively, while the correlation coefficient distances from the 0 mark and is approaching one of the two extremities (- 1 and + 1) it indicates on an increasing strength of the correlation, negative or positive respectively.

Table 5. Correlations between a selection of MFI variables and use of credit scoring or credit rating

Row	MFI characteristics	Scoring Tool			Credit Rater			Credit Scorer		
		Coef.	Sig.	N	Coef.	Sig.	N	Coef.	Sig.	N
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	Personnel #	0.28	0.000	315	0.13	0.023	307	0.23	0.000	307
2	Personnel, female #	0.27	0.000	294	0.04	0.505	286	0.29	0.000	286
3	Personnel, female %	0.13	0.021	299	-0.01	0.879	291	0.16	0.005	291
4	Staff turnover rate	-0.11	0.077	261	-0.01	0.864	253	-0.10	0.105	253
5	Loan officers #	0.23	0.000	312	0.08	0.159	304	0.21	0.000	304
6	Loan officers, female #	0.26	0.000	282	0.06	0.352	274	0.27	0.000	274
7	Loan officers, female %	0.25	0.000	287	0.06	0.312	279	0.25	0.000	279
8	Board members #	0.05	0.367	291	0.03	0.634	283	0.04	0.556	283
9	Offices (branches) #	0.19	0.001	312	-0.03	0.545	304	0.25	0.000	304
10	Other points of service #	0.21	0.002	200	-0.04	0.563	195	0.29	0.000	195
11	Gross loan portfolio (PPP)	0.30	0.000	305	0.11	0.066	297	0.27	0.000	297
12	GLP (PPP) per loan officer	0.16	0.005	302	-0.02	0.790	294	0.19	0.001	294
13	GLP of female borrowers %	0.11	0.064	291	0.09	0.124	283	0.06	0.333	283
14	GLP rural %	-0.08	0.177	283	0.05	0.430	275	-0.14	0.017	275
15	Borrowers #	0.15	0.007	313	0.00	0.979	305	0.16	0.004	305
16	Borrowers average #	0.19	0.001	290	0.01	0.857	283	0.21	0.001	283
17	Borrowers, female %	0.15	0.008	315	0.08	0.166	307	0.10	0.069	307
18	Borrowers, legal entity #	0.13	0.030	268	-0.01	0.891	260	0.15	0.016	260
19	Borrowers, urban #	0.33	0.000	283	0.06	0.337	275	0.33	0.000	275
20	Borrowers, rural #	0.00	0.966	281	-0.04	0.509	273	0.02	0.749	273
21	Borrowers, rural %	-0.13	0.035	278	0.00	0.946	270	-0.15	0.012	270
22	Borrowers, new #	0.12	0.051	244	0.01	0.876	238	0.13	0.040	238
23	Borrower retention rate	0.14	0.032	230	0.00	0.992	224	0.16	0.016	224
24	Loans #	0.19	0.001	315	-0.01	0.846	307	0.21	0.000	307
25	Loans to management and staff #	0.09	0.157	247	0.00	0.967	239	0.11	0.089	239
26	Loans to male borrowers #	0.17	0.003	304	0.00	0.932	296	0.18	0.002	296
27	Loans to female borrowers #	0.18	0.002	306	-0.02	0.735	298	0.21	0.000	298
28	Loans to female borrowers %	0.16	0.006	315	0.09	0.135	307	0.11	0.065	307
29	Borrowers per loan officer	0.08	0.167	310	-0.07	0.197	302	0.06	0.282	302
30	Borrowers per staff member	0.05	0.382	313	-0.08	0.143	305	0.08	0.161	305

Row	MFI characteristics	Scoring Tool			Credit Rater			Credit Scorer		
		Coef.	Sig.	N	Coef.	Sig.	N	Coef.	Sig.	N
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
31	Loans per loan officer	0.12	<i>0.032</i>	312	-0.09	<i>0.133</i>	304	0.13	<i>0.027</i>	304
32	Loans per staff member	0.09	<i>0.101</i>	315	-0.09	<i>0.099</i>	307	0.13	<i>0.019</i>	307
33	Depositors #	0.28	<i>0.001</i>	130	0.18	<i>0.043</i>	126	0.19	<i>0.033</i>	126
34	Depositors, corporations #	-0.09	<i>0.429</i>	75	-0.07	<i>0.542</i>	73	-0.11	<i>0.335</i>	73
35	Depositors, financial institutions #	-0.19	<i>0.102</i>	75	-0.06	<i>0.615</i>	73	-0.16	<i>0.165</i>	73
36	Depositors, retail #	0.33	<i>0.001</i>	97	0.18	<i>0.088</i>	95	0.24	<i>0.020</i>	95
37	Depositors, retail, voluntary #	0.33	<i>0.001</i>	92	0.18	<i>0.085</i>	90	0.23	<i>0.032</i>	90
38	Depositors, retail, compulsory #	0.09	<i>0.432</i>	80	0.18	<i>0.104</i>	79	-0.04	<i>0.757</i>	79
39	Deposits over GLP	-0.10	<i>0.220</i>	139	0.10	<i>0.256</i>	135	-0.18	<i>0.034</i>	135
40	Portfolio at risk 30+ days	-0.10	<i>0.079</i>	304	-0.11	<i>0.052</i>	296	-0.06	<i>0.323</i>	296
41	Portfolio at risk 90+ days	-0.10	<i>0.083</i>	305	-0.10	<i>0.073</i>	297	-0.06	<i>0.279</i>	297
42	Write-off ratio	0.09	<i>0.114</i>	291	0.05	<i>0.393</i>	283	0.03	<i>0.568</i>	283
43	Personnel expense / assets	-0.05	<i>0.445</i>	282	0.10	<i>0.098</i>	275	-0.12	<i>0.051</i>	275
44	Operating expense / assets	-0.05	<i>0.413</i>	293	0.05	<i>0.375</i>	285	-0.09	<i>0.149</i>	285
45	Administrative expense / assets	-0.05	<i>0.374</i>	291	-0.02	<i>0.739</i>	283	-0.04	<i>0.472</i>	283
46	Financial expenses / assets	0.00	<i>0.949</i>	294	-0.10	<i>0.078</i>	286	0.07	<i>0.251</i>	286
47	Financial revenues / asset	0.01	<i>0.916</i>	294	0.12	<i>0.052</i>	286	-0.07	<i>0.257</i>	286
48	Financial expense on funding liabilities / GLP	0.09	<i>0.133</i>	288	-0.10	<i>0.082</i>	280	0.13	<i>0.036</i>	280
49	Non-earning liquid assets / assets	0.09	<i>0.109</i>	301	0.04	<i>0.490</i>	293	0.08	<i>0.166</i>	293
50	Net operating income / GLP	-0.03	<i>0.640</i>	306	0.14	<i>0.016</i>	298	-0.10	<i>0.075</i>	298
51	Capital / assets	-0.17	<i>0.003</i>	306	-0.01	<i>0.899</i>	298	-0.15	<i>0.010</i>	298
52	Debt / equity	0.05	<i>0.407</i>	305	-0.03	<i>0.616</i>	297	0.03	<i>0.622</i>	297
53	GLP / assets	-0.03	<i>0.581</i>	306	0.08	<i>0.168</i>	298	-0.06	<i>0.286</i>	298
54	Fixed assets / assets	0.04	<i>0.479</i>	302	-0.07	<i>0.239</i>	294	0.10	<i>0.083</i>	294
55	Real yield on gross loan portfolio	0.04	<i>0.544</i>	297	0.07	<i>0.235</i>	289	0.01	<i>0.902</i>	289
56	ROA	0.01	<i>0.888</i>	294	0.15	<i>0.009</i>	286	-0.09	<i>0.148</i>	286
57	ROE	0.05	<i>0.426</i>	294	0.08	<i>0.202</i>	286	0.01	<i>0.810</i>	286
58	Average outstanding balance / GNI per capita	0.15	<i>0.017</i>	260	0.19	<i>0.002</i>	257	0.03	<i>0.639</i>	257
59	Average salary / GNI per capita	0.07	<i>0.259</i>	237	0.08	<i>0.214</i>	234	0.03	<i>0.669</i>	234
60	Uses poverty tool	0.05	<i>0.370</i>	278	0.00	<i>0.998</i>	272	0.07	<i>0.237</i>	272
61	Uses poverty scoring	0.15	<i>0.089</i>	124	-0.17	<i>0.069</i>	122	0.26	<i>0.004</i>	122

Abbreviations: Coef. – Pearson correlation coefficient; Sig. – statistical significance; N – number of cases; # – number; GLP – Gross Loan Portfolio; PPP – Purchasing Power Parity; ROA – Return on Assets; ROE – Return on Equity; GNI – Gross National Income.

We can observe from the first MFI characteristic presented in Table 5 that the size of the MFI in terms of number of employees (row 1) correlates positively and significantly with the use of credit scoring (Credit Scorer group), with the use of credit rating (Credit Rater group) as well as the combined group. The three positive and statistically significant coefficients indicate that MFIs that use credit scoring or credit rating tend to be larger in terms of number of employees. Correlation however doesn't imply causation. Credit scoring can help MFIs grow and give the

comfort of recruiting more junior loan officers who will have a reliable tool to help them take credit decisions or propose reasonable credit decisions to the credit committee. It could also be the opposite, larger MFIs decide to implement credit scoring because they have the budget, have a software that facilitates credit scoring implementation and use, or find it easier to systematise loan appraisal when the MFI has many loan officers spread throughout the region or the country. To demonstrate causation, one would need to have two groups of similar MFIs being collected their business indicators before treatment – implementation of credit scoring in one group, and then collect same indicators after a reasonable period of time. If the credit scoring group has, when measured second time, significantly more employees on average than the group of MFIs which did not use credit scoring, and if no other external factor has affected disproportionately one of the groups, we can conclude with a high level of confidence that the use of credit scoring leads to an increase in the size of the MFIs.

Although in the database we have datapoints capturing the business indicators of MFIs before implementation of credit scoring and after, their number is insufficient for statistically significant interpretations. Efforts to investigate direct causation have been hampered by the limitation of the available database.

Correlation doesn't always mean association. Discussed correlation coefficients observed in the first row of figures of Table 5 indicate that it has been observed that in our sample MFIs which have the status of credit scoring or credit rating users have on average more employees. However, there could be no direct link between the change in status and the growth in personnel. If, say, one regulatory organisation requires all MFIs that reach 2,000 employees to mandatorily implement credit scoring, then all MFIs with 2,000 or more employees will have credit scoring and most MFIs below the threshold might not. The positive correlation that should be observed in this hypothetical case is created artificially through external action – the legislation. Regression analysis allows for discounting the effect of captured non-related factors, such as the legislation in our example, on the association that exists between the size of the MFI and the fact that it uses credit scoring. In our study we did not measure any implication of the legislation of the surveyed MFIs. However, the fact of having many countries being represented in the sample reduces the chances of a particular, narrowly focussed legislation to bias our results.

Correlation coefficients in Table 5 indicate that the use of credit scoring correlates positively and significantly with the number and share of female employees (column 2, rows 2 and 3) the number and share of women loan officers (column 2, rows 6 and 7) and correlates negatively, although at a low statistical significance level of 10.5 percent with the staff turnover rate (column 2, row 4). These correlations are promising in that we can formulate the hypothesis that credit scoring is associated with a more gender-balanced employment strategy and the mechanism of this association might be related to the fact that when MFIs grow, they need to hire extensively. Credit scoring gives MFIs the comfort of hiring different profiles, not necessarily graduates of banking faculties who have in addition investigator abilities required to discover the true business and personal motivations of micro-borrowers. MFIs that lend mainly to women borrowers tend to hire predominantly women loan officers, but since we removed from the analysis all MFIs that have a high proportion of women borrowers, this effect should be eliminated. Regression analysis can help control for the influence of the practices of women-oriented MFIs on the possible association between the use of credit scoring and the higher rate of women employees and women loan officers in the MFIs. In many developing countries participation of women in the labour force is extremely low – a handicap that hampers the development of the country. If credit scoring can help increase the number of women working in MFIs, this would help the MFIs grow and would also help the economy to develop via two paths: provision of more financial services and higher participation of women in the labour force.

The use of credit scoring in MFIs correlates positively and significantly with different other measures of the size of the MFIs such as number of branches and number of other points of service (column 2, rows 9 and 10) the number of borrowers (at the end of fiscal year – column 2, row 15, average for the fiscal year – column 2, row 16, new borrowers financed during the fiscal year – column 2, row 22), number of borrowers legal entities (column 2, row 18), the number of loans in general and disbursed to men and to women (column 2, rows 24, 26 and 27). We have transformed the values of the gross loan portfolio (GLP) of MFIs into their corresponding purchasing power parity (PPP) equivalent to be able to compare them across countries. The gross loan portfolio of MFIs expressed in the purchasing power equivalent correlates positively and significantly with the use of credit scoring (column 2, row 11) and to a lesser extent with the use of a credit rating technique (column 5, row 11 – statistical significance of 6.6 percent).

The use of credit scoring and credit rating correlates positively and significantly with the number of depositors the MFIs have (column 2, row 33 / column 5, row 33). We could be more precise and indicate that in our sample the positive significant correlation is with the number of retail depositors (column 2, row 36) and within the retail depositors correlation is with the number of voluntary depositors (column 2, row 37), not the compulsory depositors (column 2, row 38) which one could find in MFIs that practice group lending. The MFI tests simply the repayment capacity of a group by observing the ability of group members to save for a relatively short period of time. The number of depositors is also a proxy for the size of the credit organisation. All the examples above confirm the positive correlation between the use of credit scoring and various measures of the MFI size. The use of credit rating correlates positively with only few characteristics reflecting the size of the MFI such as number of employees, number of depositors and the gross loan portfolio expressed in PPP terms.

In Table 5 several correlation coefficients involving ratio variables, which are proxies for MFI efficiency, are interesting to observe. A relevant example is the positive and significant correlation between the use of credit scoring and borrower retention rate (column 2, row 23) – retaining microfinance customers in a competitive environment requires provision of fast and constantly increasing loan amounts. Credit scoring algorithms which integrate past borrowers' behavioural characteristics facilitate the provision of fast renewal loans and should give incentives to loan officers, when the estimated credit risk is low, to issue loans approaching the maximum borrower's repayment capacity. The positive and significant correlation between the use of credit scoring and the number of loans per loan officer (column 2, row 31) and the gross loan portfolio in PPP equivalent per loan officer (column 2, row 12) indicate on an interesting hypothesis that credit scoring also helps individual loan officers be more productive in terms of loans and portfolios under management. It is worth noting that the use of credit scoring does not correlate with the number of borrowers per loan officer (column 2, row 29) indicating possibly on the hypothesis that credit scoring doesn't help loan officers get more new borrowers, but helps them provide the existing borrowers with more and larger loans.

Few correlation coefficients indicate no significant correlation between the use of credit scoring and the indicators of credit risk such as portfolio at risk (column 2, rows 40 and 41) and write-off ratio (column 2, row 42). Otherwise, correlation between the use of credit rating and the same indicators of credit risk (portfolio at risk and write-off ratio – column 5, rows 40

and 41) is negative and statistically significant at 5-7 percent. This observation could lead to the hypothesis that credit rating is good in detecting bad credit risks, but it doesn't allow MFIs to use the credit risk as a leverage to increase outreach and the efficiency of loan officers. Loan officers using credit rating can probably identify bad borrowers, but they have little confidence in the estimations of good credit behaviour.

From the remaining correlation coefficients presented in Table 5 we observe no significant correlations between the use of credit scoring and main expense and income categories of MFIs. One exception is the personnel expenses over assets (column 2, row 45) which show a negative correlation significant at 5.1 percent. If loan officers are more efficient, the loan portfolio will grow faster and respectively the assets of the MFIs will grow at a faster pace than the expenses on personnel. Similarly, if credit scoring helps employ loan officers with different profiles, the larger pool of candidates will lead to less personnel expenses in the MFI. Although this logic is in line with our previous potential hypotheses, it needs to be tested before drawing conclusions.

We notice that the use of credit scoring correlates negatively with the ratio 'capital / assets' (column 2, row 51). It means that the use of credit scoring correlates positively with the inverse of the ratio, which is 'assets / capital' – an indicator of financial leverage. The hypothesis we can formulate is that MFIs that use credit scoring are more leveraged – credit scoring would help loan officers and credit committees confidently and efficiently allocate loans. To finance new loans, when the MFI is growing, it needs to borrow more. As the leverage increases, the cost of additional funds increases. Similarly, if the MFI can take deposits, it can increase the offered interest rates to attract more depositors.

We notice that the use of credit scoring in MFIs does not show significant correlation coefficients with profit indicators such as return on assets (column 2, row 56), return on equity (column 2, row 57), yield on gross loan portfolio adjusted for inflation (column 2, row 55), and 'net operating income / GLP' (column 2, row 50). However, return on assets and net operating income over GLP correlate positively with the use of credit rating (but not credit scoring). 'Average outstanding balance / GNI per capita' (column 2, row 58 – a proxy for measuring the outreach towards poor segments of the population, the lower the indicator, the poorer the borrowers are) also correlates with the use of credit rating. The hypothesis we can formulate is

that MFIs that use credit rating focus on safer larger borrowers – fact that allows for increased operational revenues. This would be the perfect demonstration of mission drift as described in section 1.6 of the thesis. This entire thesis is built on the idea that a credit risk estimation tool needs to be used in MFIs together with a poverty assessment tool to control for and mitigate the risks of mission drift. In the same context we can observe the negative correlation coefficient, significant at 6.9 percent, resulting from the correlation analysis of the use of credit rating and poverty scoring (column 5, row 61).

Finally, the use of credit scoring correlates positively with the use of poverty scoring and does not correlate with the proxy measuring the outreach towards poorer segments of the population. It is interesting to note that the use of credit scoring correlates positively with the number of urban borrowers (column 2, row 19), but doesn't correlate with the number of rural borrowers (column 2, row 20). Urban areas provide the MFIs with faster growth opportunities in terms of more clients and bigger portfolios, but also the risk of mission drift is usually higher in cities. Our hypothesis is that MFIs that use credit scoring are larger, have a larger concentration of their portfolios in urban areas, but manage to avoid mission drift either by using poverty scoring or by focussing predominantly on their microfinance market, with the help of reliable credit scoring algorithms, which were designed to discriminate well the credit risk in the microfinance segment but not above.

4.5 The regression models

Some socio-demographic and business-demographic characteristics captured by the loan application form, many of which can be provided by the loan applicant without the intervention of the loan officer, can partially compensate for the absence of other more risk-predictive variables. Credit scoring algorithms built with 'weak' variables will show limited risk discrimination power, being able to identify only transactions with very high or very low probability of default. Other loan applications, neither too risky, nor too good, need to pass through the hands of the loan officer.

If MFIs are likely to use 'weak' credit scoring algorithms, it is reasonable to question whether the use of credit scoring helps the microlenders improve efficiency. Weak credit scoring algorithms could reduce MFI's efficiency because loan officers might spend more time

approving certain loans since they have to perform additional, credit scoring-related calculations in addition to their usual appraisal procedures.

A linear regression model (by means of ordinary least squares) is constructed. It explains MFI's outreach using a number of available variables which describe the MFI and its business environment. Once we build a strong significant regression model, we add another variable, a dummy, which indicates the actual use of credit scoring (1) or no use (0). We observe then the result of adding the scoring dummy variable. We should observe the sign (positive or negative) and the significance of the corresponding regression coefficient of the newly added variable. We should also observe how the coefficient of determination of the regression model evolves – coefficient which indicates how well our data, including the new variable, fit the model.

The basic model (Model L0) presented in Table 6 is statistically significant and has a high coefficient of determination (R Squared) indicating that selected variables in the model describe more than 95 percent of the variation of the dependent variable: number of current loans. The fact that the Adjusted R Squared (a modification of R Squared which increases only if a variable included in the model improves the R Squared more than would be expected by chance) is almost identical to the R Squared indicates that all selected variables are important for the model and the selection of variables was not random.

The number of loans in an MFI depends on the following variables that were included in the model: 'Equity' – MFI's equity expressed in thousands of US dollars; 'Debt / equity' – the ratio of debt over equity, which indicates the ability of the MFI to contract debt to serve the borrowers; 'Deposits / loans' – the ratio of volume of deposits over volume of loans, which indicates the ability of the MFI to contract deposits and identify among the depositors potential good borrowers; 'Offices' – the number of branches the MFI has, which defines the network of the financial institution; 'LO' – the number of loan officers, which represents the capacity of the MFI to treat loan applications and work with current and potential borrowers; 'Auxiliaries' – number of employees that are not loan officers, but their role is important in supporting credit operations; 'FemEffort' – represents the effort the MFIs invest in attracting more female borrowers, which is expressed through the difference between the share of female borrowers in the MFI and the share of females among the persons with formal credit in the country (source World Bank Group, 2024c; the bigger the difference, the larger the effort of

the MFI); The dummy ‘Profit’ – identifies if the MFI has profit oriented goals or acts as a NPO which does not distribute dividends; The dummy ‘REG’ – identifies if the MFI is regulated by financial supervising authorities. The last 3 dummy variables: ‘IsCreditUnion’, ‘IsBank’, and ‘IsNBFI’ – indicate if the MFI is a credit union, microfinance bank, or non-bank financial institution.

A big range of variables were dropped as their presence in the model did not improve the Adjusted R Squared. Among these variables are: the age of the MFI, portfolio at risk at 30 and at 90 days, MFI’s write-off ratio, the yield on the loan portfolio, MFI’s ROA and ROE, the average loan balance per borrower divided by the gross national income (this variable serves as a proxy for MFI’s outreach towards poorer segments of the population, the smaller the average loan, the poorer the borrowers should be). For the same cause the model does not include any variable describing the business environment, namely: the Doing Business variables (World Bank, 2017) describing the ease of getting credit in the country and the ease of starting a business, country’s gross national income per capita, GDP growth, the Gini index (measures the income distribution in the population of the country, a high index indicates high inequality in the distribution of income) and other variables measuring the level of security in the country, the use of internet and mobile phones, and the spread of ATMs.

Competition among microfinance institutions in the market is a factor that certainly influences the number of loans an MFI has. We used as proxy the share of adults that took loans the year before (source: World Bank Group, 2024c), but the variable didn’t improve the model.

Table 6. The linear regression models explaining the variation of the variable ‘Number of loans’

Row	Number of Loans	Model L0		Model L1		Model L2		Model L3	
		B	Sig.	B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	(Constant)	-40,637	0.001	-40,734	0.002	-36,333	0.001	-37,825	0.002
2	Equity	0	0.034	0	0.035	0	0.050	0	0.111
3	Debt / equity	80	0.808	79	0.810	-1	0.998	-11	0.970
4	Deposits / loans	2,182	0.877	2,254	0.873	7,802	0.534	10,521	0.420
5	Offices	979	0.000	979	0.000	1,068	0.000	1,064	0.000
6	LO	250	0.000	250	0.000	288	0.000	290	0.000
7	Auxiliaries	-47	0.001	-47	0.001	-126	0.000	-124	0.000
8	FemEffort	49,633	0.056	49,482	0.058	49,120	0.034	53,785	0.029
9	Profit	45,168	0.041	45,185	0.041	44,346	0.030	49,757	0.019
10	REG	-36,581	0.005	-36,589	0.005	-25,883	0.032	-27,613	0.035
11	IsCreditUnion	56,449	0.010	56,331	0.011	42,804	0.034	43,110	0.044
12	IsBank	17,212	0.572	16,994	0.581	31,396	0.269	21,051	0.480
13	IsNBFI	11,794	0.599	11,727	0.602	-1,643	0.936	-2,448	0.909
14	CS-User			670	0.958				
15	CS-Statistic					25,482	0.046		
16	CS-CustomMade							45,073	0.009
17	<i>Model Significance</i>	0.000		0.000		0.000		0.000	
18	<i>R Squared</i>	0.953		0.953+0.000		0.966+0.000		0.967+0.001	
19	<i>Adjusted R Squared</i>	0.951		0.951-0.001		0.965+0.001		0.965+0.001	
20	<i>Degrees of Freedom</i>	255		255		232		213	
21	<i>Scoring Users</i>			71		48		29	

We observe that adding the variable that describes if the MFI declares to use credit scoring (CS-User) does not improve the regression model (Model L1) and the regression coefficient of the variable is statistically insignificant (column 5, row 14). In the list of credit scoring users, we have two categories the ‘credit raters’, that do not use credit scoring but use a non-empirical rating tool and the ‘statistical credit scoring users’, that use credit scoring (custom-made or general).

When removing from the model the raters (Model L2) and keeping in the regression the MFIs that either do not use credit scoring [CS-Statistic = 0] or use credit scoring [CS-Statistic = 1], which is defined as an empirical tool, the variable that measures the use of credit scoring (CS-Statistic) has a positive (column 6, row 15), statistically significant (at 0.05 level) regression coefficient (column 7, row 15). The Adjusted R Squared improves slightly (+0.1 percent). We can conclude that MFIs that use credit scoring have more loans than MFIs that do not use credit scoring.

When repeating the regression in its last iteration (Model L3), keeping in the model only the non-users and the users of custom-made credit scoring tools (dummy CS-CustomMade) we observe a positive (column 8, row 16), statistically significant (at 0.01 level) regression coefficient (column 9, row 16) which is higher than the regression coefficient of the previous variable (CS-Statistic) in the previous regression model (Model L2). We conclude that MFIs which use custom-made credit scoring tools have more loans than MFIs that use non-custom-made credit scoring or do not use credit scoring at all.

In Table 7 we present the regression outcomes resulting from replacing the dependent variable ‘Number of loans’ with the variable ‘Number of borrowers’ and repeating the regression procedures keeping the same explanatory variables. In the context of microfinance both indicators are important for the outreach. More borrowers mean that financial inclusion is provided to more people, while more loans mean that some borrowers receive parallel loans and thus their financing needs are better met.

Table 7. The linear regression models explaining the variation of the variable ‘Number of micro-borrowers’

Row	Number of Borrowers	Model B0		Model B1		Model B2		Model B3	
		B	Sig.	B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	(Constant)	-38,257	0.003	-37,656	0.004	-30,649	0.006	-32,076	0.007
2	Equity	0	0.467	0	0.461	0	0.605	0	0.801
3	Debt / equity	56	0.867	59	0.859	-14	0.960	-23	0.937
4	Deposits / loans	1,774	0.901	1,339	0.926	8,857	0.469	11,357	0.373
5	Offices	1,075	0.000	1,075	0.000	1,150	0.000	1,147	0.000
6	LO	231	0.000	231	0.000	283	0.000	284	0.000
7	Auxiliaries	-40	0.005	-40	0.006	-143	0.000	-140	0.000
8	FemEffort	43,682	0.099	44,585	0.095	42,301	0.061	45,574	0.059
9	Profit	41,874	0.063	41,771	0.064	38,173	0.055	42,752	0.039
10	REG	-41,152	0.002	-41,127	0.002	-27,470	0.020	-29,361	0.022
11	IsCreditUnion	57,880	0.010	58,586	0.009	40,227	0.041	41,118	0.049
12	IsBank	14,149	0.649	15,465	0.622	32,635	0.239	24,366	0.403
13	IsNBFI	16,375	0.474	16,779	0.465	2,713	0.892	2,596	0.901
14	CS-User			-4,008	0.758				
15	CS-Statistic					19,183	0.123		
16	CS- CustomMade							34,473	0.040
17	<i>Model Significance</i>	0.000		0.000		0.000		0.000	
18	<i>R Squared</i>	0.946		0.946+0.000		0.965+0.000		0.965+0.001	
19	<i>Adjusted R Squared</i>	0.943		0.943+0.000		0.963+0.000		0.963+0.000	
20	<i>Degrees of Freedom</i>	254		254		231		212	
21	<i>Scoring Users</i>			71		48		29	

We observe that the models have similarly high R Squared and Adjusted R Squared indicators. The dummy variable ‘CS-Statistic’ (Model B2) which indicates the use of credit scoring lost its statistical (< 0.1) significance. The dummy variable ‘CS-CustomMade’ (Model B3) which indicates the use of custom-made credit scoring tool (column 8, row 16) remains statistically significant (at < 0.05 level – column 9, row 16). We can conclude that MFIs that use custom-made credit scoring tools have more borrowers than all other MFIs, all things being equal.

The manner in which a borrower reimbursed a recent loan is one of the strongest predictors of the repayment of a prospective loan. Many (behavioural) credit scoring algorithms include such behavioural variables and the MFI can approve new bigger loans even before the borrower finished to reimburse the current loan, if the borrower did not register repayment delinquencies. We believe this fact explains why the variable ‘CS-CustomMade’ has higher statistical significance in the Model L3 compared to the Model B3.

Although we have demonstrated that the users of custom-made credit scoring tools have more borrowers and disburse more loans than the non-users of credit scoring and non-users of custom-made scoring tools, we cannot prove causality because larger MFIs might be also more likely to find the required budget to implement credit scoring. Larger MFIs might be ‘forced’ to implement custom-made credit scoring tools to keep up with the demand for loans and the need to have reliable loan officers.

We also want to test if the use of credit scoring improves the productivity of the loan officers. Replacing the dependent variable in the initial regression model (Model L0) with the variable ‘Credits per loan officer’ – a ratio measuring the number of current credits over the number of loan officers – yields a model with low coefficient of determination (<10 percent). We get the same result when using the variable ‘Borrowers per loan officer’ – a ratio measuring the number of active borrowers over the number of loan officers.

We enhanced the model by dropping a few and adding other variables. The strongest regression model that we built, which does not include any variable related to the use of credit scoring, is presented in Table 8 (Model CpL0). Its R Squared is 20.7 percent and the Adjusted R Squared is 14.9 percent. The explanatory variables included in the model are: ‘Equity’, ‘Deposits / loans’, ‘Offices’, ‘LO’, ‘FemEffort’, ‘Profit’, and ‘REG’ – these variables were explained previously as they compose the models presented above. We included a new set of variables: ‘PAREffort’ – is the difference between the portfolio at risk at 30 days (PAR30 – is the share of portfolio which is overdue for more than 30 calendar days) and portfolio at risk at 90 days (PAR90), it represents the effort the MFI and its loan officers invest in reducing delinquency; ‘AvgLoanBalPerBor’ – represents the average loan balance per borrower divided by the GNI per capita (the smaller the average loan balance, the poorer are the borrowers, which take smaller loans); ‘Yield’ – represents the real yield on gross loan portfolio which is the ratio of interest plus fees on credits over the loan portfolio; ‘Gini index’; ‘CreditIndex’ is the Doing Business index (World Bank, 2017) which measures rules and practices affecting the coverage, scope, and accessibility of credit information available through either a public credit registry or a private credit bureau; ‘Homicides’ – estimates the occurrence of unlawful homicides (source World Bank Group, 2024c); and ‘SBTime’ – the Doing Business calculation (World Bank, 2017) on the total number of days required to register a firm without extra payments.

Including one at a time the dummy variables describing the use of credit scoring improves the coefficient of determination of the model (Model CpL0).

Table 8. The linear regression models explaining the variation of the variable ‘Number of credits divided by number of loan officers’

Row	Credits per loan officer	Model CpL0		Model CpL1		Model CpL2		Model CpL3	
		B	Sig.	B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	(Constant)	167.26	0.356	160.26	0.373	198.35	0.311	3.86	0.973
2	Equity	0.00	0.004	0.00	0.008	0.00	0.018	0.00	0.000
3	Deposits / loans	212.44	0.010	209.32	0.011	216.28	0.016	240.00	0.000
4	Offices	0.61	0.111	0.59	0.122	0.73	0.082	0.75	0.001
5	LO	-0.22	0.015	-0.21	0.019	-0.22	0.021	-0.20	0.000
6	FemEffort	427.98	0.001	395.30	0.001	389.24	0.004	288.35	0.000
7	AvgLoanBalPerBor	-61.09	0.042	-64.65	0.031	-61.85	0.062	-74.19	0.000
8	Profit	26.95	0.649	16.96	0.774	32.29	0.628	41.17	0.285
9	REG	-49.49	0.479	-55.59	0.424	-95.56	0.225	-36.34	0.433
10	PAREffort	107.43	0.873	-86.63	0.898	-264.22	0.714	-235.45	0.564
11	Yield	-420.35	0.019	-435.09	0.015	-427.66	0.031	-220.51	0.055
12	GINI	-0.05	0.992	0.23	0.960	0.09	0.985	2.78	0.347
13	CreditIndex	34.15	0.087	32.52	0.101	29.63	0.170	28.28	0.025
14	Homicides	-1.81	0.339	-1.78	0.344	-2.13	0.286	-1.56	0.227
15	SBTime	1.85	0.206	1.70	0.244	1.54	0.338	1.95	0.035
16	CS-User			109.53	0.056				
17	CS-Statistic					201.56	0.005		
18	CS-CustomMade							159.30	0.004
19	<i>Model Significance</i>	0.000		0.000		0.000		0.000	
20	<i>R Squared</i>	0.207		0.207+0.015		0.199+0.036		0.404+0.033	
21	<i>Adjusted R Squared</i>	0.149		0.149+0.012		0.133+0.035		0.350+0.032	
22	<i>Degrees of Freedom</i>	206		206		184		168	
23	<i>Scoring Users</i>			59		37		21	

In the Model CpL1, the variable ‘CS-User’ has a positive coefficient (column 4, row 16), with the statistical significance level < 0.1 (column 5, row 16). Both dummy variables ‘CS-Statistic’ in the Model CpL2 (column 6, row 17) and ‘CS-CustomMade’ in the Model CpL3 (column 8, row 18) show positive and statistically significant regression coefficients, with the statistical significance level < 0.01 . We note the relatively higher R Squared in the case of the Model CpL3.

We conclude that MFIs that use credit scoring, custom-made or generic, have more credits per loan officer than MFIs that do not use credit scoring.

In Table 9, we recreate the regressions using as the dependent variable ‘Borrowers per loan officer’.

Table 9. The linear regression models explaining the variation of the variable ‘Number of micro-borrowers divided by number of loan officers’

Row	Borrowers per loan officer	Model BpL0		Model BpL1		Model BpL2		Model BpL3	
		B	Sig.	B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	(Constant)	217.42	0.213	210.85	0.224	250.47	0.187	49.35	0.608
2	Equity	0.00	0.027	0.00	0.047	0.00	0.095	0.00	0.007
3	Deposits / loans	169.99	0.032	167.06	0.034	172.07	0.046	196.57	0.000
4	Offices	0.43	0.246	0.40	0.267	0.52	0.201	0.54	0.008
5	LO	-0.16	0.067	-0.15	0.085	-0.16	0.095	-0.14	0.003
6	FemEffort	394.97	0.001	364.28	0.002	354.00	0.007	246.77	0.000
7	LoanBalPerBorGNI	-51.19	0.077	-54.53	0.058	-52.67	0.100	-65.64	0.000
8	Profit	11.45	0.841	2.07	0.971	14.45	0.823	24.67	0.453
9	REG	-53.95	0.423	-59.68	0.373	-95.74	0.209	-35.32	0.372
10	PAREffort	132.08	0.838	-50.11	0.938	-204.96	0.769	-130.72	0.707
11	Yield	-375.69	0.030	-389.52	0.024	-389.21	0.042	-183.59	0.062
12	GINI	-1.13	0.800	-0.86	0.845	-0.95	0.847	2.00	0.429
13	CreditIndex	30.72	0.110	29.20	0.126	26.05	0.213	24.19	0.025
14	Homicides	-1.55	0.395	-1.52	0.401	-1.81	0.350	-1.47	0.184
15	SBTime	1.69	0.229	1.55	0.269	1.38	0.374	1.81	0.021
16	CS-User			102.83	0.062				
17	CS-Statistic					179.37	0.010		
18	CS-CustomMade							114.47	0.014
19	<i>Model Significance</i>	0.000		0.000		0.001		0.000	
20	<i>R Squared</i>	0.177		0.191		0.166+0.032		0.386+0.024	
21	<i>Adjusted R Squared</i>	0.117		0.128		0.098+0.029		0.331+0.022	
22	<i>Degrees of Freedom</i>	206		206		184		168	
23	<i>Scoring Users</i>			59		37		21	

The results of the regression analysis using as dependent variable ‘Borrowers per loan officer’, presented in Table 9, are similar to the results of the regression analysis using as dependent variable ‘Credits per loan officer’, presented in Table 8. We draw a similar conclusion: MFIs that use credit scoring, custom-made or generic, have more borrowers per loan officer than MFIs that do not use credit scoring.

4.6 Elaboration of results

By statistically modelling the number of borrowers per loan officer and the number of credits per loan officer, we established that MFIs which use credit scoring, custom-made or statistical-generic, have more productive loan officers than the MFIs that do not use credit scoring.

In many developing countries, credit bureaus do not exist or have limited access to credit data (World Bank, 2017) to be able to provide reliable credit scoring services. In such environments, custom-made solutions are the only viable option. To build a custom-made credit scoring tool, an MFI needs to have the appropriate database which includes at least a hundred bad credit risks – ideally several hundred. If only 5 percent of borrowers turn bad, it means that the MFI has to have served at least 2,000 borrowers from the same segment to collect the required number of bad credit risks. If the bad rate drops to 1 percent, then the MFI needs to serve 10,000 borrowers in a relatively short period of time, not exceeding several years.

We performed a robustness test by repeating the regressions using only mature MFIs (operating for more than five years) with more than 1,000 borrowers. We excluded from the analysis the big MFIs which have more than 500,000 current borrowers – possible outliers. The results were similar to those presented in Table 6 to Table 9 or better (in the case of Model B3), confirming the validity of our findings. We could not perform stricter robustness tests because of the low level of available degrees of freedom. The regression coefficients that we interpret and their significance are not affected by multicollinearity which produces large standard errors in the concerned independent variables (equity, loan officers, offices, and auxiliaries) but does not bias the results. We validate the assumptions of linear regression.

The use of credit scoring is associated with an increase in the number of borrowers and credits per loan officer. This suggests that credit scoring either helps MFIs grow faster or enables them to sustain an accelerated growth rate once they have already achieved loan officer efficiency. Although association does not imply causation, the direction of causality is not crucial in this context. Whether MFIs use credit scoring to become more efficient or adopt it to maintain their efficiency, the key takeaway for other MFIs and their stakeholders is that credit scoring, as an empirical credit risk assessment tool, is linked to more efficient loan officers.

Loan officers, who establish and maintain contact with potential and current clients, represent the entire credit institution with all its values and objectives, both social and financial. These loan officers are susceptible to the principal-agent problem, where their own interests may diverge from the MFI's overall strategy. Making loan officers more effective and less biased should mitigate the principal-agent problem, reducing its potential negative impact on the MFI's double bottom-line.

Sustainable growth is the only objective that can satisfy all parties: profit-maximising management, social investors, other stakeholders, and loan officers, especially when their remuneration depends on the volume and quality of the portfolios they manage. As the respective correlation coefficients were inconclusive, we did not conduct an in-depth analysis of the effects of credit scoring on portfolio quality or MFI profitability. These indicators are linked by a trade-off and should be analysed together, accounting for the time lag in the revelation of portfolio quality, as not all risky borrowers will experience severe delinquencies from the outset. When portfolio quality deteriorates, per-loan and per-pound profitability decline. However, if the MFI grows at an accelerated pace, it can still maintain or even increase profits, provided that the average per-loan profitability remains positive and the growth rate exceeds the rate at which per-loan profitability declines. The MFI may opt to sacrifice both per-loan and total profitability if growth prospects promise economies of scale, scope, and other benefits that larger institutions enjoy, such as protection from defaults by public authorities and the ability to propose and lobby for advantageous legal amendments.

However, most MFIs aim for sustainable growth. The primary advantage of credit scoring lies in its ability to generate reliable credit scores, allowing for adjustments to the approval strategy based on these scores. This enables the maintenance of a balanced approach between the speed of growth and exposure to credit risk.

Scored loan applicants are not discriminated against based on prejudice, which is an advantage over the decision of the loan officer. However, we identified one negative aspect of using credit scoring. There are inevitably good credit risks that receive scores below the approval cut-off and do not receive credit unless a loan officer overrides the approval procedure. It makes sense however to refuse certain good borrowers and with them most of bad credit risks to safeguard the sustainability of the financial institution and future microfinance operations.

The small number of credit scoring users in our sample is a limitation for this analysis. Additionally, the cross-sectional dataset we used was made static, on purpose, which prevented us from observing how outreach evolves over time in relation to the use of credit scoring. We also lack information on how predictive the credit scoring algorithms were and the extent to which the MFIs relied on these credit scores. Furthermore, we cannot rule out the possibility that some MFIs may have experienced a decline in productivity if loan officers were required

to perform additional credit scoring calculations alongside their existing appraisal procedures without gaining significant insights into the creditworthiness of loan applicants.

4.7 Chapter conclusions

Financial inclusion is the primary mission of microfinance. Since the use of credit scoring helps increase outreach and does not create mission drift, if this is not necessary to safeguard the survival of the MFI, we conclude that credit scoring contributes essentially to the mission of microfinance. This has policy implications of huge significance for all economies, but particularly so for developing nations, where financial inclusion is central to all developmental perspectives that contest each other on many other fronts.

We acknowledge that loan officers play a significant role in financing micro-borrowers. However, a lot of inefficiency and subjectivity is associated with their loan appraisal procedures. The informal environment in which microentrepreneurs operate results in high information asymmetry between MFIs and potential borrowers. Inappropriate techniques for reducing this asymmetry result in huge opportunity costs for the borrower, potential borrower, lender, and society. The use of credit scoring under certain conditions has great potential to diminish opportunity costs, increase financial inclusion, and contribute to the development of regions where MFIs operate.

MFIs rely on credit scoring to grow faster in a sustainable manner. Credit scoring is thus the accelerator pedal which can maintain a sustainable mix of growth and credit risk exposure, and can thus become a critical tool for expanding financial inclusion and developmental opportunities.

Chapter 5 Poverty scoring and financial inclusion of the poor

Microfinance is often criticised for mission drift (Aitken, 2013; Bateman, 2012). Such criticisms are valid only if non-poor applicants also tend to apply for and receive microloans. To prevent this, microfinance institutions need tools that help identify and prioritise the poor. One such solution is poverty scoring (Schreiner, 2010b). This chapter explores how poverty scoring is integrated into the microfinance sector.

5.1 Introduction

In general, income is an indicator of a person's degree of poverty or prosperity. Any society needs to know about people living in poverty in order to provide them with welfare and other benefits, such as financial inclusion. Poverty leads to financial exclusion for several reasons: financial services are too expensive for the poor (Dupas and Robinson, 2013; Prina, 2015); those with modest incomes are denied financial services (Simpson and Buckland, 2009); and some poor people exercise self-restraint because of the fear and shame of possible refusal (Jennett *et al.*, 2012). Financial exclusion penalises people, thus contributing to the vicious cycle of poverty. Financially excluded people cannot get appropriate financing for making the smallest investment: improving living conditions, paying for education to secure a job, or buying productive assets, for example. It is even more dramatic when a working poor person, who temporarily runs out of money, has no overdraft facility and no possibility of borrowing some money for food or medicine.

Although poverty, when measured using income, is a continuous variable, it is commonly dichotomised using a cut-off point. People or households with incomes above the cut-off are considered non-poor, while the rest are deemed poor. Most developing countries use either a national poverty line – an income cut-off point specific to the country – or the international extreme poverty line calculated by the United Nations, which is used extensively by the largest developmental agencies worldwide.

The concept of an international extreme poverty line was introduced in 1990. Because it is denominated in US dollars, conversion to local currencies is done using purchasing power parities, which are particular exchange rates adjusted for relative price differences across

countries. These adjustments allow for accurate comparisons of extreme poverty levels across countries and enable the estimation and tracking of the global poverty headcount. The 1990 extreme poverty line used purchasing power parity from 1985.

Due to inflation, the World Bank has reviewed the international poverty line several times since 1990. Initially, it was set at 1 US dollar per person per day, calculated for all countries using 1985 purchasing power parity (PPP). The first adjustment increased it to 1.08 US dollars per person per day using the 1993 PPP. The second adjustment set it at 1.25 US dollars using the 2005 PPP. The third adjustment established it at 1.90 US dollars per person per day using 2011 PPP (Ferreira *et al.*, 2015). In 2022 (the last known adjustment), the international poverty line was set at 2.15 US dollars using 2017 PPP (Jolliffe *et al.*, 2022).

These 2.15 US dollars represent the purchasing power in the US in 2017. This international poverty line must be adjusted for inflation and the corresponding purchasing power parity when applied to different countries and years. The international extreme poverty line assumes that a person's basic needs can be met in 2017 with 2.15 PPP dollars per day (Jolliffe *et al.*, 2022). People or households with average daily per capita incomes below this extreme poverty line are considered extremely poor and are counted when national and global extreme poverty levels are measured.

The World Bank estimated that just over 900 million people experienced extreme poverty in 2012 (Ferreira *et al.*, 2015). This figure declined from 1.93 billion in 1981 to 1.3 billion in 2008 (Chen and Ravallion, 2010). The global extreme poverty rate fell further when it was measured again in 2017. It decreased from an estimated 9.3 percent in 2012 to 9.1 percent in 2017, reducing the number of people considered extremely poor by 15 million (Jolliffe *et al.*, 2022).

The latest World Bank Group (2024c) estimations reveal that in 2022, approximately 712 million people worldwide lived below the international poverty line of 2.15 dollars per day (at 2017 PPP). The consequences of the Covid-19 pandemic caused the first increase in global extreme poverty in 25 years. Extreme poverty increased from 8.9 percent in 2019 to 9.7 percent in 2020, driven significantly by South Asia. In 2022, global poverty was still marginally above pre-pandemic levels but on a declining trend. About 23 million more people were living in extreme poverty in 2022 compared to 2019 estimates (World Bank Group, 2024c).

Additionally, Russia's 2022 full-scale invasion of Ukraine contributed to rising food and energy prices worldwide, with dramatic consequences for vulnerable populations in low- and middle-income countries.

The measurement of poverty and identification of the poor in developing countries pose several problems because of the widespread existence of informal and semi-formal sectors (Schneider and Enste, 2000), which can both underestimate as well as overestimate the scale of poverty (Harriss-White, 2003). Underestimation of poverty can result from corrupt bureaucrats and business people registering property and banking accounts on poor nominee persons. Overestimation of poverty can result from entrepreneurs underreporting income in order to diminish tax liability and avoid drawing the attention of corrupt bureaucrats. It can also result from business entities not formally hiring employees or reporting in the payroll only fractions of their effective salaries in order to reduce employer contributions (Dabla-Norris *et al.*, 2008). When poverty is overestimated, considerable proportions of the population qualify for social benefits, including those who are not poor due to their reported incomes being small.

Many families in developing economies live off remittances sent by migrant workers. Such remittances, if sent through informal channels or if not verifiable by tax authorities, do not get reported as income despite their important contribution to the family budget (Singh and Velásquez, 2013). The chances are high that such families are not poor by local standards, but for the state authority they qualify as poor or extremely poor. Such information asymmetry entitles non-poor families to claim welfare.

These complexities do not imply that there is no widespread poverty and extreme poverty in developing countries. In fact, many of those who are not currently poor are vulnerable to being poor due to internal or external shocks (Bhusal, 2012). Nevertheless, these complexities hinder the process of identification of the real poor who desperately need access to welfare benefits and financial inclusion.

Institutions involved in providing welfare benefits and financial inclusion, such as MFIs, therefore, need robust mechanisms to identify the real poor. The best technique for identifying the poor would certainly be to assess each individual person or household separately using financial diaries such as those implemented by Collins, Morduch, Rutherford, and Ruthven

(2009) or long questionnaires to estimate different income sources of applicants, but this is expensive and time consuming. The costs of estimating poverty and identifying the poor can be reduced by using poverty scoring. A poverty scoring algorithm is built using structured data derived from a substantial investment in reliable and representative income assessments. These may include national poverty assessment surveys or other representative surveys designed to estimate real household income levels and identify characteristics that can predict income levels without directly measuring income or expenditure. Consequently, only a few specific characteristics of applicants for welfare benefits or financial inclusion need to be observed to accurately estimate whether they are poor or not.

In this chapter, we empirically test whether the use of poverty scoring by MFIs is associated with increased social outreach, that is, the provision of financial inclusion to a larger share of poor clients. We further test whether the use of poverty scoring by MFIs is associated with lower financial costs that MFIs pay for borrowing funds. Such an association would indicate that social investors financing MFIs value the use of poverty scoring by MFIs and are, therefore, willing to provide them cheaper financing.

5.2 Who needs poverty scoring and why?

Using a representative sample of surveyed households, one can extrapolate the poverty level and income distribution in a country. However, this does not identify exactly who in the country is poor and who is not, it only provides a general picture. This is where poverty scoring comes in. It can be used to identify rapidly, with a certain degree of accuracy, poor households or individuals who need to be targeted for welfare benefits or financial inclusion.

It is in the interest of institutions that provide welfare benefits or subsidised services that without spending a major part of their budget on extensively surveying their applicants, they are able to reach the really poor. People who are not poor by local standards may often apply for welfare benefits. In conditions of information asymmetry, institutions that cannot verify each individual claim can use poverty scoring for screening the poor from the non-poor or, if exclusion is not desirable, measure the real share of poor beneficiaries and adjust, if necessary, the outreach strategy to target bigger shares of poor people.

Some easily observable characteristics of a household can be helpful in differentiating a poor family from a non-poor one without performing a full income assessment of the household (Schreiner, 2010b). For example, if in a village a house has walls made of clay instead of stone or bricks, a tin roof instead of a tiled or concrete roof, one common room instead of many, and does not own any cattle, it seems to be good evidence of the household being poor. Therefore, using statistical procedures and structured data of such type, one can construct an algorithm which estimates the chances of a person with a certain profile to have revenues below an established limit.

Based on an initial sample of responses to a questionnaire, the poverty scoring developer determines the characteristics which differentiate the poor from the non-poor, isolating the importance of each relevant characteristic. This individual importance is usually expressed with a number – the characteristic's score. Using the algorithm (which is generally based on a scorecard) yields an aggregate score which is associated with a probability of the subject being poor. For example, if the aggregate score of a person applying to receive subsidised services is 80 in a particular algorithm, it may be associated with 90 percent chance that the applicant is poor. If the score was 95 in the same algorithm, it may be associated with 70 percent (lower) chance that the applicant is poor. Dichotomisation is made by applying a cut-off score. If such a cut-off would be set at 85 points, the former applicant with 80 points would be classified as poor, but the applicant with 95 poverty scoring points would be classified as not poor and either rejected or, if rejection is not possible or desirable, reported as a non-poor beneficiary.

There are costs associated with the use of poverty scoring tool as with any tool. Some costs are operational, related to the implementation, use, and maintenance of the scoring tool. Others are opportunity costs relating to some non-poor applicants being characterised as poor (the false positives) while others who are poor being categorised as non-poor (the false negatives). If no tool were to be used, there would be no operational costs, but there would still be such opportunity costs.

Many microfinance institutions do not deny credit based on the poverty score, but screen non-creditworthy applicants. The use of poverty scoring allows the institutions to estimate the proportion of poor among the applicants and loan recipients. These metrics, if outreach towards

the poor is high, might represent an asset for the microfinance institutions which can signal to social investors interested in poverty reduction to get funding from them.

One other big advantage of poverty scoring is the ability to track recipients' scores over time and thus measure their progress out of poverty. If the average poverty score of long-term clients increases with time (the probability of poverty decreases), it would demonstrate that the average income of loan recipients increased and some are no longer poor or are less poor than before. MFIs may attribute this poverty reduction to the impact of financial inclusion facilitated by them.

To summarise, microfinance institutions may need poverty scoring to: 1. screen off applicants – refuse some clients if their profiles indicate low probability of being poor; 2. evaluate post-factum the percentage of poor micro-borrowers, and 3. track the progress out of poverty of microloan recipients – an indicator of possible objective social impact of provided financial inclusion.

5.3 Potentialities and limitations of poverty scorecards

The construction of poverty scoring algorithms, similar to credit scoring, requires statistical modelling and appropriate data, including both a training sample and a test sample. Statistical modelling involves using multivariate analysis techniques to generate one or more classification algorithms from the training sample. The test sample is then used to ensure that these algorithms consistently assign high scores to non-poor subjects and low scores to poor subjects (or vice versa, depending on the preferences of the poverty scoring developer) without prior knowledge of their income level. Based on these tests, the best algorithm is selected for implementation and use.

Obtaining the training and test samples demands a lot of effort since poor and non-poor households have to be extensively surveyed, first to determine accurately their income, and second, to collect various poverty-related characteristics out of which a manageable number, say a dozen, can be identified for the purpose of composing poverty scoring algorithms.

Some MFIs might already have collected their own data needed for development of poverty scoring algorithms because when loan officers evaluate loan applications, they make detailed assessment of income and expenditure of micro-borrowers. Loan application forms require,

and thus collect, social, business, and demographic information. If the MFIs can get complete data about a few hundred confirmed poor loan applicants and a few hundred confirmed non-poor applicants, and if this sample is representative of the population that applies for MFI's loans, then these data can be used for statistical modelling. It is important to mention here that there are limitations to the use of poverty scoring algorithms because the availability of data does not guarantee that the algorithms will have sufficient discrimination power to justify their use. That is an unavoidable risk which any scoring technique has to bear.

Governments of many developing countries systematically organise national household income and expenditure surveys. Data from such surveys are used for developing poverty scorecards (see Schreiner, 2011).

The choice of indicators to be included in national poverty scoring algorithms can have social implications, since those classified as non-poor might not have access to welfare benefits. For example, in 2013 there were media reports (newspaper "Timpul de dimineață" of April 01, 2013) about social tensions which led the Government of Moldova to amend the official poverty scorecard by excluding 3 out of 17 characteristics from the official poverty scoring algorithm, which seemed unjust or unclear to different segments of population for the use of these characteristics for classifying households as poor or non-poor. These characteristics were: possession of a black and white television in rural area, possession of bicycle in rural area, and possession of a telephone.

Martinelli and Parker (2009) found that applicants in a poverty alleviation program in Mexico were systematically underreporting certain household characteristics to appear poorer than they actually were in order to increase their chances of getting into a poverty-alleviation program. It was also noted that they were reporting certain non-existent characteristics, such as availability of sanitation infrastructure, in order to not appear embarrassingly poor for social reasons. This example of contradictory behaviour on the part of the poor in underreporting some and overreporting other characteristics highlights the difficulty in constructing robust poverty scoring algorithms and their use. Therefore, the developers of poverty scoring algorithms and their users have to be vigilant. For example, it may appear that observing whether a household owns a television is an easy task, but it may turn out to be very difficult if the householder hides the television.

Societal changes also affect the usefulness of a poverty scorecard for classifying households as poor or non-poor (Desiere *et al.*, 2015). For example, in many developing countries the possession of a mobile phone a few years ago signified a well-off economic status, while currently the advances in telecommunication technologies, by reducing costs, have enabled many poor households to get access to mobile phones. Therefore, each scorecard needs to evolve with social changes.

Since statistical modelling is a scarce and expensive skill, several open-source initiatives have emerged. We can cite here the internet portals microfinance.com (2024) and progressoutofpoverty.org (Innovations for Poverty Action, 2024). These initiatives offer free, reliable poverty scorecards for 76 developing and developed countries, focussing mainly on countries severely affected by extreme poverty.

From this discussion one would expect that:

- Hypothesis 1 – MFIs that use poverty scoring show increased social outreach; and
- Hypothesis 2 – MFIs that use poverty scoring have lower financing costs than similar MFIs by attracting social investors and donors that provide them cheap financing.

5.4 Regression analyses

5.4.1 Hypothesis 1 – poverty scoring is associated with increased social outreach

To test if the use of poverty scoring in MFIs is associated with increased outreach towards the poor, we construct a linear regression model using ordinary least squares. Since only MFIs that use poverty scoring, or similar poverty measurement and approximation tools, can estimate and report the number of poor borrowers they serve, while non-user MFIs cannot, we use a proxy which estimates the depth of the outreach level towards poor borrowers. This proxy, which is the dependent variable, measures the average loan balance per borrower expressed in PPP dollars: ‘AVGLoanPPP’. We calculate this variable using MFIs’ average loan balance per borrower provided by the MIX Market database (World Bank Group, 2024b) and purchasing power parity (PPP) conversion rates which are used for calculating the PPP gross domestic product of countries (World Bank Group, 2024c). The lower the average loan balance expressed in PPP dollars in the MFI, the poorer are its borrowers. Such borrowers have in

general reduced repayment capacity due to low levels of disposable income, which can be the result of low income or high levels of debt.

In some countries, regulators impose caps on loan amounts that microfinance institutions can issue. In Morocco, for example, the microfinance sector is regulated. MFIs however are allowed and often encouraged to issue entrepreneurial loans to informal businesses. The cap on microloans has been fixed at MAD 50,000 (about EUR 4,500) for decades. However, a decree (Bulletin Officiel du Royaume du Maroc, 2019) increased the cap threefold, but only for entrepreneurs who have certain formal registration, including cooperative members. Such caps allow poor entrepreneurs to borrow relatively small amounts to sustain their informal businesses. However, when the borrowing capacity increases – a sign that the business is growing and generating greater disposable income – the micro-borrower is encouraged to formalise in order to access larger loans.

A growing informal business in Morocco can borrow small loans for informal income generation activities simultaneously from several MFIs, meeting the need for larger financing. However, this practice cannot remain unnoticed by the MFIs, which report the loans they issue monthly to the national credit bureau. To speed up the dissemination of information on new clients and avoid over-indebtedness or fraud, large MFIs in Morocco share a file with the names of current clients. Although no official source can be cited about the existence of this file and principles of dissemination, MFIs presumably share this information at a much more frequent pace than the credit bureau to spot multiple borrowers sooner. Early 2024 statistics in Morocco show that the average loan outstanding in MFIs is MAD 11,500 (about EUR 1,000) – well below the cap for informal businesses of MAD 50,000. This average also includes the microloans to formal businesses, which have had a higher cap of MAD 150,000 since 2019 and represent 5 percent of total microloans in the country (Fédération Nationale des Associations de Microcrédit, 2024).

In other countries, MFIs are not encouraged to issue entrepreneurial loans because informal entrepreneurship is prohibited. These MFIs, like in the case of Moroccan MFIs issuing entrepreneurial loans to informal businesses, will issue a *de facto* personal loan. The business owner and eventual co-signers will be liable for reimbursing the loan in case the informal

business defaults. The amount of the personal loan will be proportional to the income level of the entrepreneur, whether this income is formal or informal.

The reflection from above supports the idea that the average loan balance per borrower expressed in PPP dollars is a good proxy for the share of poor borrowers MFIs serve. Conversion to PPP dollars makes this proxy suitable for cross-country comparisons. The biggest advantage of this proxy is that it is expressed in dollars considering each country's purchasing power. One such dollar buys, in the same year, the same amount of goods and services in each country. The international extreme poverty line is expressed in PPP dollars also.

Explanatory variables concern legal status, MFI's business and financial indicators and some macroeconomic indicators of the country. Among the explanatory parameters we have the variables which record the use of poverty assessment tools such as poverty scoring. In fact, we construct three dummy variables. One dummy variable captures the information if the MFI measures the poverty of its clients: 'PM-User'. Two other dummy variables are used to identify the type of poverty assessment the MFIs use, if they measure poverty. Dummy 'PM-Scorer' identifies MFIs that use poverty scoring. Dummy 'PM-Rater' identifies MFIs that use any other poverty measurement tool which is not based on statistical algorithms constructed using multivariate analysis.

We selected the explanatory variables based on availability and judgement. Since used or potential variables are not available for all MFIs and all countries, often adding a new variable to the regression model results in losing several records from the regression. This approach is similar to the one presented in Chapter 4.

We try to build a strong, significant regression model without the dummy variables describing the use of poverty measurement in the MFI. Once we have the model, we add to the initial regression model, one dummy variable, then we add the second dummy, while keeping the first dummy in the model. The first dummy indicates if a poverty measurement tool is used in the MFI [PM-User = 1] or not [PM-User = 0]. The second dummy indicates which type of poverty measurement tool it is. Is it poverty scoring [PM-Scorer = 1] or not [PM-Scorer = 0]? We do not need a third dummy, which would indicate that the poverty measurement tool is not poverty

scoring but an alternative tool [PM-Rater = 1]. In fact, when the poverty measurement tool is poverty scoring [PM-User = 1 and PM-Scorer = 1], the dummy ‘PM-Rater’ is necessarily ‘0’.

We observe the effects of adding the dummy variables to the basic regression model. We pay attention to the sign (positive or negative) and the significance of the corresponding regression coefficient. We should also observe how the coefficient of determination (R squared) of the regression model and its improved version (Adjusted R squared) evolve. These coefficients indicate how well the used data, including the new variables, fit the model.

In our regression, as in previous analyses from above, we eliminate extreme outliers. We use the number of employees of the MFI to identify outliers. If we had used the number of active borrowers, total assets, or portfolio size to identify outliers instead of the number of employees, we could unfairly penalise large and efficient MFIs. These MFIs might serve a significant number of borrowers with relatively few employees, unlike very large MFIs that have both a high number of active borrowers and a substantial number of employees, including loan officers. Extremely large or very small MFIs could distort the analysis by skewing the observed averages.

Outliers at the right of the distribution have a number of employees greater than the 3rd quartile + three times the interquartile range – the range between 25 and 75 percentiles. Table 10 presents relevant percentiles and quartiles of the distribution of the number of employees of the MFIs in our database for the year 2014. In that year 990 MFIs worldwide provided information on poverty measurements and type of used tool, within the social performance measurements of the Mix Market initiative (World Bank Group, 2024b). In 2015 only 46 MFIs volunteered such data. 913 MFIs volunteered poverty measurement data in 2013 and 759 in 2012. The data from years 2013 and 2012 are used to test the robustness of the regression models presented in this chapter.

Table 10. Distribution across percentiles of MFIs by the number of employees in the database (year 2014)

Percentiles	5	10	25	50	75	90	95
Personnel	13	21	52	173	613	1,787	2,862
Interquartile range			x	-	x		

Interquartile range = $613 - 52 = 561$. Extreme outliers have personnel above $613 + 3 \times 561 = 2,296$ employees. 44 MFIs have been excluded out of the total 598 records (out of 990 records, only 598 records had data on the number of employees for the year 2014).

To identify outliers on the left-hand side of the distribution, we excluded a similar number of records as we did on the right-hand side – 44 records. These records consisted of MFIs with between 2 and 15 employees. Traditionally, a fully established MFI would not have such a small number of employees, although advancements in artificial intelligence and cloud computing suggest the possibility of a fully digital MFI operating with minimal staff while serving an entire country. However, for MFIs to effectively reach and expand their outreach to financially excluded individuals, loan officers remain crucial, as financial and computer literacy are closely linked. Despite the increasing penetration of smartphones and tablets among poor populations, poverty continues to pose a significant barrier to acquiring modern gadgets essential for digital banking and similar services. For the year 2014, 554 records remained in the regression analysis. Since not all variables were available for each record, the regression analysis, depending on the selected variables, used only those records where all required variables were available. No treatment of missing variables was conducted.

The basic regression model ‘Model AVG0’ presented in Table 11 is statistically significant and has a high coefficient of determination (R Squared) indicating that selected variables in the model describe more than 44 percent of the variation of the dependent variable (the average loan balance per borrower expressed in PPP dollars). The fact that the Adjusted R squared (a modification of R Squared which increases only if a variable included in the model improves the R Squared more than would be expected by chance) is not much different from the R Squared indicates that selected variables are important for the model and the selection of variables was not random.

Dependent variable: average loan balance per borrower, expressed in PPP dollars ‘AVGLoanPPP’ – this is the outcome variable in the initial regression model and its two additional iterations.

Explanatory variables include:

- ‘Size: $\ln(\text{borrowers})$ ’: this calculated variable is the natural logarithm of the number of active borrowers in the MFI. As MFIs grow, they produce economies of scale and become visible to local and national public authorities, but also to national and international development partners. The natural logarithm better mimics the impact of the size on economies of scale and market relevance of MFIs than the size alone;
- ‘% individual lending’: this variable represents the percentage of loans issued individually, as opposed to through group lending practices. Group lending can be more cost-effective and efficient for serving a large number of poor borrowers with very small loan amounts, as it leverages borrowing groups to manage tasks such as borrower selection and repayment enforcement. While group lending has proven that poor borrowers are creditworthy and can form a viable credit market, it may not be suitable for all microentrepreneurs, especially those who need larger loans and may not benefit from group-based lending. In our previous regression models, we excluded MFIs with a high proportion of group lending because it is challenging to apply credit scoring effectively in this context. We kept such MFIs in the current regressions since MFIs that practice group lending may be more inclined to use poverty scoring and measure the poverty level of their clients;
- ‘% female borrowers’: indicates the percentage of female borrowers, capturing the MFI’s efforts to reach women, who often face greater financial exclusion. This variable, often also used as a proxy for outreach towards poorer borrowers, in combination with ‘% individual lending’, helps control for variations in average loan balance due to a focus on female borrowers with or without group lending practices. One should expect a decrease in the average loan balance as the percentage of female borrowers increases. One should expect an increase in the average loan balance as the percentage of individual lending increases;
- ‘Borrowers / loan officers’: this ratio describes the outreach efficiency of the MFI. An outreach-efficient MFI is expected to have a higher proportion of poorer borrowers as poorer borrowers are more numerous and their relatively small business size allows for faster loan uprisal and disbursement;

- ‘Deposits / loans’: the variable represents the ratio of volume of collected deposits over volume of the gross loan portfolio. The variable measures the MFI’s ability to attract deposits. MFIs which are allowed to take deposits should be more inclined to lend to lower-income borrowers. Some of these borrowers could be low-income clients who show ability to save regularly. One could expect a decrease in the average loan balance in the MFI as the volume of deposits increases;
- ‘Operating expense / assets’: the ratio accounts for MFIs with high operating costs that might be focussed, on purpose or not, on smaller loans. One expects to observe lower average loan balances associated with higher operating expense ratios and *vice versa*;
- ‘Financial expense / assets’: this ratio controls for MFIs that incur high financial costs. These MFIs might target borrowers who accept to pay higher interest rates. One expects to observe lower average loan balances associated with higher ratios. Larger borrowers who take larger loans expect to pay lower interest rates, while smaller, poorer borrowers, who are more affected by financial exclusion, are willing to pay higher interest rates, making lending viable in conditions when financial expenses are high;
- ‘Financial revenue / assets’: the ratio, strongly correlated with the previous ratio, equally helps control for MFIs’ orientation towards poorer segments when they can charge higher interest rates. The ratio also includes the margin the MFI charges. One expects to observe lower average loan balances associated with higher ratios;
- ‘Credit union’: dummy variable indicating whether the MFI is a credit union. The type of the credit institution generally influences the MFI’s business model and operational structure;
- ‘NBFI’: dummy variable indicating if the MFI is a non-bank financial institution;
- ‘NPO’ (non-profit organisation): dummy variable indicating if the MFI is a non-profit organisation. Non-profit MFIs are expected to cater to poorer borrowers. One expects to observe lower average loan balances associated with MFIs registered or operating as NPOs;

- ‘Rural bank’: dummy variable indicating whether the MFI operates as a rural bank. Rural banks often face different regulations compared to mainstream commercial banks, which are intended to facilitate lending in rural and underserved areas, where the concentration of poor populations tends to be higher than in urban or peri-urban areas. As a result, one would expect to observe lower average loan balances associated with rural banks. In fact, the dummy ‘Bank’ – the last of the dummies describing the type of MFI – has been removed from the regression in accordance with the requirements of the analysis technique. The removed dummy serves as the baseline against which the effect of all other dummies describing the MFI type (‘Credit union’, ‘NBFI’, ‘NPO’, and ‘Rural bank’) on the dependent variable should be measured. All dummies describing MFI types other than ‘Bank’ are expected to register lower average loan balances when compared to the baseline;
- ‘Per capita GDP (PPP)’: describes the per capita GDP of the country in PPP dollars. This variable controls for national poverty levels, influencing the average loan balance. One expects to observe lower average loan balances associated with MFIs operating in poorer countries;
- ‘PAR30’ (portfolio at risk over 30 days): the variable represents the share of the portfolio overdue for more than 30 days over the total volume of the gross loan portfolio. This variable reflects the quality of the portfolio. An MFI confronted with a deteriorating portfolio might reduce lending, especially lending to clients who are perceived as more risky or more difficult to serve;
- ‘Debt / equity’: the ratio of debt to equity, indicates the MFI’s ability to attract debt to support lending activities. A higher ratio could indicate that the MFI has access to financing, which can be used to serve relatively smaller borrowers after all relatively larger borrowers have been served;
- ‘# social goals’: variable which counts how many non-financial social goals the MFIs declares to target. In addition to usual social goals centred on financial inclusion of women, youth and small businesses, the database included a list of non-financial goals such as: improvement of adult education, children’s schooling, health improvement and access to water and sanitation that MFIs could declare to target. Pursuing such goals, even if on a

declarative level, requires some communication or outreach effort. Vulnerable people might be attracted to such MFIs, lowering the average wealth of the pool of potential borrowers. An MFI declaring more goals should have poorer clients.

- ‘PM-User’: dummy variable indicating whether the MFI uses a poverty measurement tool. It is expected, as the hypothesis goes, that the variable is associated with lower average loan balance per borrower, expressed in PPP dollars; and
- ‘PM-Scorer’: dummy variable indicating whether the poverty measurement tool used is poverty scoring. This variable is only applicable if ‘PM-User’ is 1, otherwise, it is missing. It is expected that this variable will be associated with lower average loan balances. The dummy ‘PM-Rater’, which indicates whether the poverty measurement tool is an alternative to poverty scoring and is not based on statistically derived algorithms, has been removed, as it is the inverse of ‘PM-Scorer’. When one dummy is 1, the other must necessarily be 0. The regression coefficient of ‘PM-Rater’, if included in the regression instead of its inverse, would be identical to the regression coefficient of ‘PM-Scorer’, but with the opposite sign.

Were dropped from the regression model regional dummies: ‘In Africa’, ‘In East Asia and the Pacific’, ‘In Eastern Europe & Central Asia’, ‘In Latin America & the Caribbean’, ‘In the Middle East & North Africa’, and ‘In South Asia’. These dummy variables represent the region where the MFI operates. These variables were reducing the Adjusted R squared coefficient.

Table 11. The linear regression models explaining the variation of the variable ‘Average loan balance per borrower expressed in PPP dollars (AVGLoanPPP)’

Row	AVGLoanPPP (year = 2014)	Model AVG0		Model AVG1		Model AVG2	
		B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)
1	(Constant)	17,148	0.000	17,545	0.000	17,531	0.000
2	Size: <i>ln</i> (borrowers)	-761	0.000	-761	0.000	-761	0.000
3	% individual lending	468	0.414	389	0.497	410	0.479
4	% female borrowers	-4,002	0.000	-3,798	0.000	-3,791	0.000
5	Borrowers / loan officers	-1.5	0.053	-1.1	0.177	-1.1	0.174
6	Deposits / loans	-657	0.312	-911	0.163	-897	0.171
7	Operating expense / assets	-6,791	0.004	-6,817	0.004	-6,816	0.004
8	Financial expense / assets	1,361	0.829	3,193	0.609	3,063	0.625
9	Financial revenue / assets	-5,370	0.038	-5,430	0.034	-5,427	0.035
10	Credit union	-2,453	0.003	-2,187	0.012	-2,213	0.011
11	NBFI	-2,024	0.004	-1,737	0.014	-1,734	0.014
12	NPO	-3,314	0.000	-2,996	0.000	-3,000	0.000
13	Rural bank	-1,585	0.409	-946	0.656	-962	0.651
14	Per capita GDP (PPP)	0.13	0.000	0.11	0.000	0.11	0.000
15	PAR30	-758	0.811	-1,741	0.598	-1,730	0.601
16	Debt / equity	17	0.625	16	0.643	16	0.634
17	# social goals	-30	0.826	-19	0.887	-21	0.878
18	PM-User			-1,163	0.007	-1,220	0.011
19	PM-Scorer					136	0.784
20	<i>Model significance</i>	<.001		<.001		<.001	
21	<i>R squared</i>	0.436		0.445		0.446	
22	<i>Adjusted R squared</i>	0.409		0.415		0.413	
23	<i>Degrees of freedom</i>	350		325		325	

The regression analysis is conducted first without using the poverty measurement dummies: resulting in the initial model ‘Model AVG0’. The regression is conducted in two additional iterations: ‘Model AVG1’ and ‘Model AVG2’. Resulting regression coefficients for all three iterations are presented in ‘B’ columns (columns 2, 4 and 6) and the significance of these coefficients are presented in ‘Sig.’ columns of Table 11 (columns 3, 5 and 7).

For each iteration, the significance of the model iteration is presented in row 20. Values of R squared and Adjusted R Squared are presented in rows 21 and 22, respectively. The number of datapoints used in the regression (degrees of freedom) are presented in row 23.

The robustness of each regression model was tested using data from years 2013 and 2012, which had a large number of records. Before 2012 and after 2014 the number of records was

significantly lower. The regression coefficients of our dummy variables maintained their sign and statistical significance when changing the year of analysis but also when incorporating different control variables.

We observe that the dummy variable ‘PM-User’, which indicates whether an MFI uses a poverty measurement technique, has a negative (column 4, row 18) and statistically significant regression coefficient (column 5, row 18). Specifically, MFIs using a poverty measurement technique have an average loan balance per borrower that is 1,163 dollars lower than MFIs that do not use such a technique, holding all other factors constant. This finding suggests, without implying causality, that MFIs using a poverty measurement technique tend to reach out to poorer borrowers than MFIs which are not using a poverty measurement technique. This conclusion validates hypothesis 1 and partially supports the findings of a previous study, which used social performance data collected by the author under the initiative of the Banque Populaire Chair in Microfinance at the Burgundy School of Business and was published in Bumacov *et al.* (2017). In Bumacov *et al.* (2017) it was found that only not-for-profit MFIs using a poverty measurement technique had a lower average loan balance per borrower. Conversely, for-profit MFIs that used poverty scoring or alternative poverty measurement techniques had higher average loan balances per borrower, with only the coefficient for using poverty scoring being statistically significant at the $P < 0.05$ level. In the regressions presented in Table 11, the for-profit dummy was not included because the Mix Market database (World Bank Group, 2024b) only contained the most recent for-profit status of the MFI and because the type of the MFI generally correlates with the for-profit or not-for-profit status.

Other statistically significant coefficients presented in Table 11 confirm the validity of the regression model iterations. From expected associations the following have been confirmed: variable ‘% female borrowers’ is associated with lower average loan balance per borrower, expressed in PPP dollars; variable ‘Borrowers / loan officers’ is associated with lower average loan balance per borrower; variable ‘Deposits / loans’ is associated with lower average loan balance per borrower; the dummy variables ‘Credit union’, ‘NBFI’, and ‘NPO’ are associated with lower average loan balance per borrower; ‘Per capita GDP (PPP dollars)’ is associated with lower average loan balance per borrower; and variables ‘Financial revenue / assets’ and ‘Operating expense / assets’ are also associated with lower average loan balance per borrower expressed in PPP dollars.

The size of the MFI (variable ‘Size: $\ln(\text{borrowers})$ ’) is associated with lower average loan balance per borrower expressed in PPP dollars.

We conclude that the use of poverty measurement techniques in MFIs is associated with increased outreach towards the poor. The fact that the used poverty measurement technique is precisely poverty scoring does not indicate an association with even lower average loan balance per borrowers. It means that the poverty measurement technique is irrelevant for the outreach effort towards the poor, as long as the MFI uses one. The regression coefficient corresponding to the dummy ‘PM-Scorer’ (column 6, row 19) is positive, but it has no statistical significance. One should know that when the dummy ‘PM-Scorer’ is replaced with ‘PM-Rater’ the regression coefficient of ‘PM-Rater’ is the negative of ‘PM-Scorer’, while the statistical significance is the same. This is because the dummy ‘PM-Rater’ is the inverse of the dummy ‘PM-Scorer’.

5.4.2 Hypothesis 2 – poverty scoring is associated with reduced financial expense

We expect to find that MFIs using poverty scoring have lower financial expenses compared to their peers that do not use poverty scoring, all other things being equal, because poverty scoring users attract or retain social investors and donors. Financiers oriented towards poverty reduction are likely to offer cheaper financing to MFIs that achieve specific social objectives. The use of poverty scoring helps reinforce the MFIs’ role in contributing to social goals, such as poverty reduction.

We construct a linear regression model in which ‘Financial expense / assets’ – financial charges experienced by the MFI divided by the value of its assets – depends on several factors, including the use of a poverty measurement technique. Table 12 presents the regression results of the model. We control also for the social outreach level ‘AVGLoanPPP’ – the variable created for the previous regression. Additionally, a new variable, ‘Non-earning liquid assets / assets’, is included in the analysis. This variable helps control for increased financial expenses that occur when overleveraged MFIs, which do not receive cheaper financing but instead obtain additional funds at market prices for their social initiatives, draw down immediately the needed resources before allocating them to the targeted end-beneficiaries – poorer borrowers.

Table 12. The linear regression models explaining the variation of the variable ‘Financial expense / assets’

Row	Financial expense / assets (year = 2014)	Model FE0		Model FE1		Model FE2	
		B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)
1	(Constant)	0.036	0.042	0.034	0.076	0.033	0.080
2	Size: <i>ln</i> (borrowers)	0.001	0.470	0.001	0.362	0.001	0.377
3	% individual lending	-0.005	0.364	-0.006	0.268	-0.005	0.348
4	% female borrowers	0.002	0.837	0.002	0.816	0.003	0.793
5	Borrowers / loan officers	0.000	0.215	0.000	0.179	0.000	0.164
6	Deposits / loans	-0.004	0.440	-0.005	0.419	-0.004	0.467
7	Financial revenue / assets	-0.039	0.062	-0.041	0.056	-0.041	0.056
8	Credit union	0.102	0.000	0.101	0.000	0.101	0.000
9	NBFI	0.005	0.526	0.007	0.391	0.006	0.473
10	NGO	0.005	0.461	0.005	0.423	0.005	0.419
11	Rural Bank	-0.008	0.210	-0.007	0.324	-0.007	0.310
12	AVGLoanPPP	-0.019	0.244	-0.018	0.350	-0.019	0.336
13	Per capita GDP (PPP \$)	0.000	0.693	0.000	0.512	0.000	0.528
14	Debt / equity	0.000	0.075	0.000	0.044	0.000	0.058
15	PAR30	-0.028	0.299	-0.021	0.477	-0.021	0.488
16	Debt / equity	0.001	0.000	0.001	0.001	0.001	0.001
17	# social goals	-0.018	0.011	-0.017	0.016	-0.017	0.020
18	Non-earning liquid assets / assets	0.000	0.983	0.000	0.963	0.000	0.926
19	PM-User			0.000	0.938	-0.002	0.668
20	PM-Scorer					0.005	0.247
21	<i>Model significance</i>	0.000		0.000		0.000	
22	<i>R squared</i>	0.191		0.188		0.191	
23	<i>Adjusted R squared</i>	0.152		0.143		0.146	
24	<i>Degrees of freedom</i>	349		324		324	

We observe that the use of a poverty measurement technique in general and poverty scoring in particular is not associated with lower financial expense. In fact, the use of poverty scoring might be associated with higher financial expense. We can reject hypothesis 2.

We cannot prove that MFIs attract cheaper financing from social investors when using poverty scoring or any alternative poverty measure tool. The question remains why MFIs use poverty scoring?

It is worth noting that the use of a poverty measurement tool in general, and one based on the poverty scoring technique in particular, is not associated with lower operational expenses. The regression analysis – similar to the one presented in Table 12 but not shown in a separate table – reveals no statistically significant association between the variable ‘Operating expense /

assets' and the dummies coding the use of a poverty measurement tool in general, or poverty scoring in particular.

5.4.3 Trying to resolve the paradox

On one hand, we observe that the use of poverty scoring is associated with increased outreach towards poorer borrowers. On the other hand, MFIs that use poverty scoring do not register lower costs of financing. Why then do MFIs use poverty scoring? Some MFIs, especially those operating as non-profit organisations, might choose to implement poverty scoring on their own or be obliged by their socially-oriented stakeholders. But why would for-profit MFIs use poverty scoring if it does not help the institutions lower their cost of financing?

Cheaper funding from social investors is one benefit that MFIs can receive if they demonstrate their ability to reach and finance poorer borrowers, or show significant outreach figures. However, this research was unable to quantitatively prove this hypothesis. Another key benefit that social investors can provide to MFIs is the availability of additional funding when MFIs are highly leveraged and unable to secure financing from traditional market players. Providing extra funding to highly leveraged MFIs at current market rates benefits both the MFIs and their clients. Since the funding is offered at market rates, this practice should not create market tensions. These highly leveraged MFIs are expected to be efficient and effective in lending, with interest rates for end-borrowers in line with those of other MFIs, including non-profits, despite the absence of subsidised funding. Their profit-oriented nature, irrespective of their for-profit status, drives them to optimise operations, increase outreach, and, willingly or not, increase impact. Providers of additional funding to highly leveraged MFIs assume a higher credit risk, but since social investors expect lower returns in exchange for higher social outcomes, the difference between expected returns and the actual interest rates at which the funds are provided may help offset the increased risk of lending to highly leveraged institutions.

Available data on MFIs, which were used in this research, does not include details on the structure of borrowed funds and different costs associated with diverse funding sources. Only total annual cost of all funding was available for most MFIs. However, we can possibly detect if MFIs have access to increased financing by observing the share of non-earning liquid assets MFIs hold. MFIs that have access to extra financing at a certain point in time will be inclined to draw down funds in excess of their current needs. Excess funds will appear in MFIs'

accounts as non-earning liquid assets. Similarly, if social investors provide funding reserved for poor borrowers identified through poverty scoring, these funds will be disbursed to the MFI but will be on-lent to poor borrowers only when appropriate candidates apply for loans. In the meantime, the reserved funds will appear in MFIs' accounts as non-earning liquid assets.

Initially, we constructed a regression model using data collected under the initiative of the Banque Populaire Chair in Microfinance at the Burgundy School of Business, where the dependent variable was 'Non-earning liquid assets / assets' – the value of non-earning liquid assets divided by the value of total assets. This variable was introduced in a previous regression. Regression results, published in Bumacov *et al.* (2017), showed that the use of poverty scoring by for-profit MFIs was associated with higher shares of non-earning liquid assets. Similar results have been found for non-profit MFIs using alternative poverty measurement techniques. These observations led to the conclusion that, regardless of the direction of causality, poverty scoring serves as both a poverty measurement technique and a signal to social investors that user-MFIs can target poorer borrowers. If funding is extended to these MFIs, they will be able to prove that these funds have been on-lent to poorer borrowers or predominantly to poorer borrowers. Non-profit MFIs, which naturally have more access to subsidised funding, also use poverty measurement techniques, but these techniques do not necessarily need to be statistically derived to prove empirically to stakeholders that the MFI remains committed to serving poorer segments of the population.

Using social performance data from the Mix Market database (World Bank Group, 2024b), the hypothesis that MFIs which use poverty measurement tools have higher shares of non-earning liquid assets could not be proved.

Using same, social performance data, from the Mix Market database, the hypothesis that MFIs which use poverty measurement tools are overleveraged could not be proved either. The leverage in financial institutions is represented by the ratio 'Debt / equity'. The variable measuring debt over equity is not associated with the use of a poverty measurement technique in MFIs. The variable 'Debt / equity' is not associated with the use of a poverty scoring either.

Table 13 presents the linear regression model in which return on assets (RoA) depends on several factors, including the use of a poverty measurement technique.

Table 13. Regression which models return on assets

Row #	RoA (year = 2014)	Model RoA0		Model RoA1		Model RoA2	
		B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)
1	(Constant)	0.013	0.294	0.012	0.366	0.012	0.370
2	Size: <i>ln</i> (borrowers)	-0.001	0.155	-0.001	0.192	-0.001	0.190
3	% individual lending	0.005	0.167	0.004	0.308	0.004	0.288
4	% female borrowers	0.002	0.778	-0.002	0.725	-0.002	0.734
5	Borrowers / loan officers	0.000	0.534	0.000	0.736	0.000	0.752
6	Deposits / loans	0.006	0.135	0.006	0.153	0.006	0.147
7	Operating expense / assets	-0.927	0.000	-0.927	0.000	-0.927	0.000
8	Financial expense / assets	-0.944	0.000	-0.943	0.000	-0.944	0.000
9	Financial revenue / assets	0.838	0.000	0.846	0.000	0.846	0.000
10	Credit union	0.005	0.333	0.007	0.200	0.007	0.220
11	NBFI	0.005	0.233	0.006	0.156	0.006	0.155
12	NPO	0.016	0.001	0.017	0.000	0.017	0.000
13	Rural bank	-0.006	0.579	-0.001	0.953	-0.001	0.945
14	AVGLoanPPP	0.000	0.255	0.000	0.353	0.000	0.350
15	Per capita GDP (PPP \$)	0.000	0.169	0.000	0.119	0.000	0.131
16	Debt / equity	0.000	0.328	0.000	0.345	0.000	0.337
17	PAR30	-0.082	0.000	-0.091	0.000	-0.091	0.000
18	Non-earning liquid assets / assets	0.007	0.167	0.006	0.214	0.006	0.208
19	# non-financial goals	-0.001	0.119	-0.001	0.085	-0.001	0.083
20	PM-User			0.004	0.137	0.003	0.244
21	PM-Scorer					0.001	0.683
22	<i>Model significance</i>	<i><.001</i>		<i><.001</i>		<i><.001</i>	
23	<i>R squared</i>	<i>0.941</i>		<i>0.943</i>		<i>0.943</i>	
24	<i>Adjusted R squared</i>	<i>0.938</i>		<i>0.940</i>		<i>0.940</i>	
25	<i>Degrees of freedom</i>	<i>349</i>		<i>324</i>		<i>324</i>	

The iterations of the regression model ‘RoA’ presented in Table 13 show that the use of a poverty measurement tool is positively associated with MFIs’ RoA ratio – regression coefficient of the variable ‘PM-User’ (column 4, row 20), however, the statistical significance exceeds the acceptable level of $P < 0.1$.

We note that nearly 95 percent of the variation in the return on assets (RoA) of an MFI is determined by factors such as portfolio quality (PAR30), the type of institution (particularly NPOs), operating expenses, financial expenses, financial revenues, and commitment to achieve non-financial goals. The use of a poverty measurement technique is associated with higher RoA ratios, but the statistical significance threshold is not met.

Available data show that the use of poverty measurement tools in MFIs is associated with higher returns on equity, suggesting that MFIs that decide to implement poverty scoring or simpler alternatives might get different sets of benefits, that could not be observed individually, from a statistical point of view, considering data limitations, but which, together, result in improved profitability of their equity. These benefits might not be observed through improved profitability of assets since marginal lending becomes more expensive when the financial institution is overleveraged, driving the average profitability down, while total profitability continues to increase, but at a much slower rate.

Table 14 presents the linear regression model in which return on equity (RoE) depends on several factors, including the use of a poverty measurement tool.

Table 14. Regression which models return on equity

Row #	RoE (year = 2014)	Model RoE0		Model RoE1		Model RoE2	
		B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)
1	(Constant)	0.149	0.882	-0.241	0.824	-0.237	0.827
2	Size: $\ln(\text{borrowers})$	0.118	0.111	0.129	0.110	0.129	0.109
3	% individual lending	-0.751	0.008	-0.803	0.008	-0.812	0.008
4	% female borrowers	-1.840	0.000	-2.057	0.000	-2.061	0.000
5	Borrowers / loan officers	0.000	0.328	0.000	0.455	0.000	0.450
6	Deposits / loans	-0.453	0.150	-0.435	0.202	-0.440	0.198
7	Operating expense / assets	-2.510	0.030	-2.336	0.060	-2.334	0.060
8	Financial expense / assets	-4.998	0.103	-5.246	0.109	-5.197	0.114
9	Financial revenue / assets	3.639	0.004	3.981	0.003	3.981	0.003
10	Credit union	0.298	0.464	0.487	0.282	0.499	0.274
11	NBFI	0.048	0.887	0.119	0.747	0.118	0.749
12	NPO	-0.074	0.842	0.011	0.979	0.013	0.974
13	Rural bank	0.409	0.657	0.560	0.611	0.567	0.607
14	AVGLoanPPP	0.000	0.812	0.000	0.617	0.000	0.615
15	Per capita GDP (PPP \$)	0.000	0.560	0.000	0.487	0.000	0.476
17	PAR30	1.653	0.279	2.256	0.188	2.252	0.190
16	Debt / equity	0.008	0.654	0.008	0.662	0.008	0.671
18	Non-earning liquid assets / assets	-0.277	0.483	-0.258	0.531	-0.263	0.525
19	# non-financial goals	0.056	0.393	0.057	0.411	0.058	0.407
20	PM-User			0.390	0.086	0.414	0.100
21	PM-Scorer					-0.058	0.823
22	<i>Model significance</i>	<i>.024</i>		<i>.020</i>		<i>.028</i>	
23	<i>R squared</i>	<i>0.089</i>		<i>0.102</i>		<i>0.102</i>	
24	<i>Adjusted R squared</i>	<i>0.040</i>		<i>0.046</i>		<i>0.043</i>	
25	<i>Degrees of freedom</i>	<i>349</i>		<i>324</i>		<i>324</i>	

Results of the regression show that the use of a poverty measurement tool in MFIs is associated with higher return on equity (column 4, row 20). The statistical significance of the coefficient indicating this positive association is 0.086 which is within the limits of $P < 0.1$.

The use of poverty scoring, as one of the most accurate techniques to estimate fast the poverty level of a large number of people, makes no difference as long as a poverty measurement tool is in place. We should mention that, in sharp contrast with RoA-related regression analysis, RoE-related regression model iterations presented in Table 14 have low coefficients of determination. This suggests that other factors, including random variations, account for about 90 percent of the variation in RoE. The use of a poverty measurement tool is one of the explanatory factors, maintaining the direction (sign) of the association and statistical

significance ($P \leq 0.1$) when controlling for additional factors such as RoA, extreme poverty (using the rate of children not in primary school as a proxy) and the share of donated equity.

We retain that, regardless of the direction of the causality, the use of a poverty measurement technique is associated with significant increase in the return on equity. The association is statistically significant.

The increase in RoE could be the result of a mixture of benefits that MFIs receive when they signal to stakeholders that they measure the poverty of their borrowers and thus could, not only prove that a certain share of portfolio is issued to poorer borrowers, but deliberately target poor borrowers.

Higher returns on equity, associated with the use of poverty measurement techniques, could also be explained by a more careful spending policy implemented by MFIs that want to signal their commitment to the social mission of microfinance. Non-profit MFIs have incentives to increase spending on salaries and alternative forms of remuneration for top managers when they generate profits that cannot be distributed. For-profit MFIs may also experience such incentives, but these are generally tempered by the institution's owners.

5.5 Chapter conclusions

In this chapter, we confirm that the use of a poverty measurement tool is associated with increased outreach to poor borrowers in MFIs. If this tool is based on the poverty scoring technique or another, less accurate one, seems to make no difference. Without implying causality, the regression analysis shows that MFIs using a poverty measurement tool have lower average loan balances per borrower, expressed in PPP dollar terms. MFIs that serve a larger proportion of poor borrowers register lower average loan balances per borrower. Similarly, an MFI that serves the same proportion of poor borrowers, but whose borrowers are relatively poorer, will also register lower average loan balances per borrower. The policy implications for this conclusion centre on MFI stakeholders, who should incentivise MFIs to adopt poverty measurement techniques. Encouraging the use of these techniques can help MFIs better target and serve poorer segments of the population, thereby enhancing financial inclusion. Particular focus should be drawn to poverty scoring which is an empirical poverty

measurement technique that helps avoid the bias or bad intentions of loan officers and loan applicants, when they want to manipulate the income level of loan applicants and borrowers.

A robust poverty measurement technique supports the relevant data collection and analysis. Such data can help MFIs and their stakeholders, who support financial inclusion, develop new financial and non-financial products. It also simplifies the monitoring and evaluation of the impact of these products or social programmes, which can be integrated with broader social welfare initiatives for a more comprehensive approach to poverty alleviation. Furthermore, robust poverty measurement data can help the industry identify and share best practices and success stories of MFIs that successfully reach poorer borrowers. Demonstrating significant outreach to poor clients can potentially alleviate compliance and regulatory pressures, allowing MFIs to focus more on their mission of reaching the poor rather than being burdened by the increased costs of compliance.

Attempts to find proof of economic reasons why MFIs would implement poverty scoring have failed. This question was particularly relevant for profit-oriented MFIs, which might not be constrained by their owners or partners like non-profit MFIs are. We found that the use of a poverty measurement tool is neither associated with lower cost of funding (expressed through the variable ‘Financial expense / assets’), nor with lower operating costs (variable ‘Operational expense / assets’). We found that the use of a poverty measurement tool was not associated with access to additional funding (variable ‘Non-earning liquid assets / assets’). We found that the use of poverty measurement tools is associated with increased return on equity. We found that the use of a poverty measurement tool is associated with increased return on assets, however the statistical significance of this association is below the fixed threshold of $P \leq 0.1$.

The increased profitability of equity could be explained by the aggregate effect of different benefits that MFIs get from social investors, donors, and other stakeholders when MFIs signal ability to measure the poverty level of their borrowers and capacity to stay committed to the social mission of microfinance. The increased profitability of equity could be explained also by a more careful spending policy implemented by MFIs that want to signal their commitment to the social mission of microfinance.

Further research is needed to provide definitive answers to the speculations outlined above. Such research would require a different set of MFI-level data, including detailed information about the various sources of funding and their costs, as well as more comprehensive data on the subsidies and donations – both in-kind and cash – that MFIs receive from their stakeholders.

Chapter 6 The joint use of credit scoring and poverty scoring

In the initial chapters of this thesis, we demonstrated theoretically the necessity for MFIs to jointly use credit scoring and poverty scoring to avoid both types of adverse selection. Unlike mainstream financial institutions, which must avoid risky borrowers to remain sustainable, MFIs also need to avoid non-poor borrowers. While wealthier borrowers do not pose a threat to the financial bottom-line like uncontrolled credit risk does, they threaten the MFI's social mission – the social bottom-line. Double bottom-line institutions require bidimensional management tools to prevent mission drift and ensure sustainability. One dimension is profit, while the other is the social mission of serving the financially excluded. The combined use of poverty scoring and credit scoring enables MFI management to adjust business strategies to control credit risk while pursuing the mission of providing financial inclusion to the poor. The combined use of poverty scoring and credit scoring enables loan officers to make credit decisions which are in line with the poverty- and profit-related goals of the credit institution.

6.1 Introduction

This chapter statistically explores the commonalities and differences between MFIs that use both a poverty measurement technique and credit scoring, those that use only one of these methods, and those that use neither.

We demonstrate that credit scoring is associated with increased outreach to all borrowers. With the same number of loan officers, all else being equal, MFIs using credit scoring, or a similar credit rating technique, can serve more borrowers. We have also shown that MFIs using poverty scoring or a similar poverty measurement technique, all else being equal, reach out to poorer borrowers than MFIs which do not measure poverty with an appropriate tool. Since credit scoring helps increase the number of clients with various poverty profiles, as long as their credit transactions fit the MFI's accepted credit risk, it is reasonable to question whether the joint use of credit scoring and poverty scoring is associated with increased social outreach.

It is also reasonable to question whether the combined use of credit scoring and poverty scoring is associated with increased profitability. If stakeholders offer distinct advantages to MFIs that

use poverty scoring, and if credit scoring enhances loan officer productivity, it stands to reason that these two effects together could lead to increased profitability.

6.2 The joint use of credit scoring and poverty scoring, and social outreach

We revisit the regression model developed in Section 5.4.1. We add to regression model iterations ‘AVG1’ and ‘AVG2’ presented in Table 11, in several iterations, variables describing the use of credit scoring. The variables describing the use of a poverty measurement technique are already part of the models ‘AVG1’ and ‘AVG2’. The new model iterations, presented in Table 15, have simultaneously the two types of variables: the ones describing the use of poverty scoring and the ones describing the use of credit scoring.

Table 15. The linear regression models explaining the variation in the variable ‘Average loan balance per borrower expressed in PPP dollars’ including through variables indicating the use of credit scoring and the use of poverty measurements tools

Row	AVGLoanPPP (year = 2014)	Model AVG3		Model AVG4		Model AVG5	
		B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)
1	(Constant)	17,832	0.000	17,594	0.000	16,819	0.000
2	Size: $\ln(\text{borrowers})$	-257	0.221	-232	0.267	-265	0.218
3	% individual lending	-963	0.272	-1,005	0.253	-610	0.513
4	% female borrowers	-5,415	0.001	-5,536	0.001	-5,840	0.001
5	Borrowers / loan officers	-6	0.004	-6	0.004	-7	0.002
6	Deposits / loans	409	0.755	404	0.759	66	0.960
7	Operating expense / assets	9,974	0.087	10,019	0.087	10,345	0.083
8	Financial expense / assets	19,897	0.047	19,073	0.059	20,560	0.046
9	Financial revenue / assets	-19,314	0.001	-19,333	0.001	-19,200	0.002
10	Credit union	-4,008	0.001	-4,027	0.001	-3,767	0.003
11	NBFI	-3,574	0.001	-3,569	0.001	-3,827	0.000
12	NPO	-4,445	0.000	-4,371	0.000	-4,353	0.000
13	Rural bank	-627	0.843	-462	0.884	707	0.824
14	Per capita GDP (PPP)	0.09	0.027	0.09	0.035	0.11	0.018
15	PAR30	-2,177	0.508	-2,337	0.480	-2,106	0.532
16	Debt / equity	-40	0.297	-38	0.329	-31	0.434
17	# social goals	-8	0.963	-22	0.896	-59	0.733
18	PM-User	-1,251	0.041	-1,206	0.049		
19	CS-User	-713	0.179				
20	CS-Empiric			-646	0.283	-585	0.342
21	PM-Scorer					452	0.470
22	<i>Model significance</i>	<.001		<.001		<.001	
23	<i>R squared</i>	0.589		0.586		0.570	
24	<i>Adjusted R squared</i>	0.506		0.502		0.483	
25	<i>Degrees of freedom</i>	107		107		107	

The model iteration ‘AVG3’ presented in columns 2 and 3 of Table 15 includes both variables: ‘PM-User’ (row 19) and ‘CS-User’ (row 20). ‘PM-User’ is a dummy variable that indicates whether an MFI uses a poverty measurement tool. ‘CS-User’ is the dummy that indicates whether the MFI uses credit scoring or credit rating, the latter being a similar technique but not based on strict multivariate analysis as credit scoring is, allowing a higher degree of bias when classifying loan applications as good or bad credit risks. Here and throughout the thesis, we use the term ‘credit scoring’ for both credit scoring and credit rating, as there is no other widespread term to be used when dealing with both credit estimation techniques together.

We note that the regression coefficient of the variable ‘PM-User’ maintains the sign (column 2, row 18) and statistical significance (column 3, row 18) revealed initially in the regression iteration ‘Model AVG0’ from Table 11, when the variable ‘CS-User’ is added to the model. The added variable ‘CS-User’ also has a negative regression coefficient (column 2, row 19). The statistical significance of the coefficient (column 2, row 19) falls short of the $P \leq 0.1$ level, which we have fixed as the maximum acceptable for statistically significant associations. Nevertheless, it is highly likely that with a slightly larger number of data points representing MFIs using credit scoring, the ‘CS-User’ variable would have shown a negative and statistically significant regression coefficient.

We conclude that the joint use of a poverty measurement technique and credit scoring is associated with greater outreach to poor borrowers. For MFIs that use both techniques, the two negative coefficients are summed, resulting in a much lower average loan balance per borrower expressed in PPP dollars. For joint users, the average loan balance per borrower is smaller, all things being equal, than in MFIs that use either of the techniques, and definitely much smaller than in MFIs that use neither poverty measurement nor credit scoring.

The model iteration ‘AVG4’ presented in columns 4 and 5 of Table 15 replaces the dummy variable ‘CS-User’ with ‘CS-Empiric’. ‘CS-Empiric’ identifies MFIs that use credit scoring but not a credit rating technique. The results were almost identical to those of the model ‘AVG3’. The reason for including the dummy ‘CS-Empiric’ in regressions throughout this research is to observe the impact on the dependent variables of the use of credit scoring, but not credit rating. Credit scoring is a technique based on algorithms which, if developed correctly with the appropriate historical data and used properly, provides accurate credit risk estimations superior to any other non-statistical credit risk estimation technique, such as credit rating.

The credit risk estimation effect represented by the dummy ‘CS-Empiric’ on the predicted variables should be so strong when credit risk is relevant that the regression coefficient should be statistically significant even when the dummy ‘CS-User’ is not used. When ‘CS-User’ is not used in the regression but ‘CS-Empiric’ is, the effect of credit scoring (‘CS-Empiric’) is measured against non-users and users of credit rating, combined.

We have not applied the same principle when using in regression analysis the dummies describing the use of a poverty measurement technique. The reason for having different approaches for poverty measurement dummies and credit scoring dummies is that any poverty measurement technique will estimate, to a certain degree of accuracy, the poverty level of borrowers. The financial cost of misclassifying a non-poor borrower as poor is probably negligible. With credit scoring and alternative credit risk estimation techniques, the situation is different. Non-statistical techniques can induce significant bias, leading to a higher degree of misclassification among loan applicants. The financial cost of misclassifying a good credit risk as bad is non-negligible – the MFI loses the opportunity to serve a good borrower and to make some profit on the transaction. The financial cost of misclassifying a bad credit risk as good is often an order of magnitude higher. Therefore, weak credit risk estimation tools can create additional losses rather than reduce them. Since MFIs that declared the use of a credit risk estimation tool not based on statistical multivariate analysis, which we classified under ‘credit rating’ (‘variable ‘CS-Rater’), are more likely to use a weak tool, we do not use the dummies ‘CS-User’ and ‘CS-Rater’ together. Because the variable ‘CS-Rater’ is the inverse of the variable ‘CS-Empiric’, we do not use the dummies ‘CS-User’ and ‘CS-Empiric’ together either.

The last model iteration, ‘AVG5’, presented in columns 6 and 7 of Table 15, replaces the dummy ‘CS-User’ with ‘CS-Empiric’ and ‘PM-User’ with ‘PM-Scorer’. The dummy ‘PM-Scorer’, introduced previously, identifies the MFIs that use strictly poverty scoring – a poverty measurement technique based on statistics. The results of iteration ‘AVG5’ are inconclusive with respect to the association between social outreach and the joint use of credit scoring (strictly) and poverty scoring. This particular model iteration, in which the dummy variables ‘PM-Scorer’ and ‘CS-Empiric’ identify the true users of poverty scoring and credit scoring, reveals the association between the joint use of credit scoring and poverty scoring and the variable measuring the social outreach of MFIs.

It was hoped that, since both scoring techniques are based on statistical multivariate analysis and can accurately identify poor and creditworthy borrowers, such MFIs could sustainably achieve the highest level of outreach to ‘poor & safe’ borrowers. However, due to the low incidence in our database, and probably also in the microfinance industry, of MFIs that use true

credit scoring with true poverty scoring, we could not observe a meaningful association between the true joint use of credit scoring and poverty scoring and social outreach.

Nevertheless, we have shown that the joint use of credit scoring (including credit rating) and a poverty measurement technique is associated with increased social outreach. Without implying causality, the negative association between the use of a poverty measurement tool in an MFI and its average loan balance has been proven statistically. The negative association between the use of a credit risk estimation tool in an MFI and its average loan balance can be observed but cannot be statistically proven at maximally acceptable significance levels.

The lack of statistical significance does not prevent us from issuing policy recommendations that MFIs should be encouraged and incentivised to implement both credit scoring and poverty scoring, and use them jointly when deciding whether to approve or reject a loan application, as well as when deciding on the outreach strategy of the institution. There is no doubt that credit scoring is an effective and efficient technique for identifying bad credit risks. Used alone, but preferably as a decision support tool for loan officers, credit scoring helps make unbiased credit decisions, increasing access to finance for segments of the population that are denied access to financial services for reasons such as poverty or other discriminatory factors.

6.3 The joint use of credit scoring and poverty scoring, and MFI costs

Since credit scoring and poverty scoring algorithms extract knowledge from large databases and concentrate it in mathematical formulas, it was initially hoped to observe lower relative operating costs in MFIs that use jointly credit scoring and poverty scoring. Proper implementation of both tools would require an initial investment, however, afterwards, loan officers and supporting personnel can make important economies when estimating the poverty level and credit riskiness of loan applicants.

Regression analysis could not confirm this hypothesis. A deeper analysis provides insights into why the variable ‘Operating expense / assets’ is not negatively associated with the joint use of poverty scoring and credit scoring, both when definitions are strict or not (include non-empiric variations).

A loan officer will save time in estimating the poverty level of a loan applicant when using poverty scoring, especially if the MFI needs an accurate estimation and has no algorithm for it. Without poverty scoring, the loan officer will have to accurately estimate the income of the microenterprise and the individual revenues of household members who have other income sources. The loan officer might need to observe the assets of the business and the material possessions of the household to confidently state that a loan applicant has revenues above the poverty line.

A loan officer using poverty scoring will spend more time dealing with a loan applicant than a loan officer who is not obliged to estimate the poverty level of the same loan applicant. Cost reductions can be observed only in MFIs that switch from direct estimation of poverty to estimation using poverty scoring. MFIs that switch from no poverty estimation to poverty scoring or similar techniques will incur increased costs.

Even if a well-developed poverty scoring tool is based on only a dozen easily observable indicators, these need to be observed and collected. If loan applicants have a literacy rate allowing them to independently fill in their poverty assessment forms, some poverty scoring indicators will still need to be explained by loan officers to applicants for accuracy. Some self-provided indicators might need double-checking, since loan applicants tend to manipulate sensitive information such as income and the availability of sanitation in the household.

It is worth noting that loan officers, in any case, will try to estimate the revenues of the loan applicant in order to calculate the disposable income and, based on this, to structure the prospective loan. The quality of these estimates remains low as loan applicants, willingly or not, will manipulate these figures in their effort to obtain a larger loan amount. Loan officers often do not have the time, knowledge, or tools to make these estimates accurate.

After issuing a very small loan initially, a rule of thumb many loan officers use is to gradually increase the loan amount after each successful repayment. An anticipated repayment might hint at a more substantial increase in the next loan, while several repayment delinquencies would suggest no increase or a reduction in the loan amount or instalment. Some borrowers manage to game the system. They take new, slightly larger loans to repay their old loans. After a few iterations, they manage to obtain large loans on which they default, sometimes on purpose, and

sometimes because the process of securing larger loans is expensive, time-consuming, and may divert the attention of the micro-borrowers away from their income-generating activities.

We note here that hopes of finding lower financial expenses in MFIs that use credit scoring with poverty scoring were also in vain.

Other hypotheses which could not be confirmed are: MFIs which use poverty scoring with credit scoring have higher shares of non-earning liquid assets and MFIs which use poverty scoring with credit scoring are highly leveraged – variable ‘Debt / equity’.

6.4 The joint use of credit scoring and poverty scoring, and return on assets

We revisit the regression model ‘RoA1’, which is presented in Table 13. We add to that initial model, in several iterations, variables describing the use of credit scoring. The variables describing the use of poverty scoring have already been included in the ‘RoA1’ model.

The new model iterations, presented in Table 16, have simultaneously two types of variables: the ones describing the use of poverty scoring and the ones describing the use of credit scoring.

Table 16. The linear regression models explaining the variation in return on assets including through variables indicating the use of credit scoring and the use of poverty measurement tools

Row	RoA (year = 2014)	Model RoA3		Model RoA4		Model RoA5	
		B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)
1	(Constant)	0.004	0.860	0.004	0.881	0.010	0.681
2	Size: $\ln(\text{borrowers})$	0.000	0.807	0.000	0.984	0.000	0.942
3	% individual lending	0.008	0.199	0.008	0.199	0.008	0.243
4	% female borrowers	0.009	0.458	0.007	0.550	0.008	0.509
5	Borrowers / loan officers	0.000	0.404	0.000	0.321	0.000	0.345
6	Deposits / loans	-0.012	0.218	-0.010	0.284	-0.008	0.385
7	Operating expense / assets	-0.712	0.000	-0.710	0.000	-0.710	0.000
8	Financial expense / assets	-0.816	0.000	-0.837	0.000	-0.838	0.000
9	Financial revenue / assets	0.680	0.000	0.680	0.000	0.675	0.000
10	Credit union	0.009	0.325	0.008	0.371	0.006	0.530
11	NBFI	0.000	0.994	0.000	0.996	0.000	0.973
12	NPO	0.011	0.204	0.011	0.169	0.010	0.214
13	Rural bank	0.019	0.401	0.017	0.445	0.012	0.572
14	AVGLoanPPP	0.000	0.866	0.000	0.861	0.000	0.631
15	Per capita GDP (PPP \$)	0.000	0.568	0.000	0.361	0.000	0.401
16	Debt / equity	0.000	0.259	0.000	0.366	0.000	0.342
17	PAR30	-0.074	0.002	-0.078	0.001	-0.079	0.001
18	Non-earning liquid assets / assets	-0.024	0.263	-0.026	0.214	-0.027	0.201
19	# non-financial goals	-0.001	0.405	-0.001	0.243	-0.001	0.277
20	PM-User	0.005	0.280	0.005	0.216		
21	CS-User	-0.010	0.007				
22	CS-Empiric			-0.014	0.001	-0.015	0.001
23	PM-Empiric					0.002	0.697
24	<i>Model significance</i>	<.001		<.001		<.001	
25	<i>R squared</i>	0.849		0.857		0.854	
26	<i>Adjusted R squared</i>	0.814		0.823		0.821	
27	<i>Degrees of freedom</i>	106		106		106	

The model iteration ‘RoA3’ presented in columns 2 and 3 of Table 16 includes both: the variable ‘PM-User’ (row 20) and the variable ‘CS-User’ (row 21). We note that the regression coefficient of the variable ‘PM-User’ maintains the sign revealed initially in the regression model ‘RoA1’ (Table 13) when the variable ‘CS-User’ is added to the model. The notable finding is the negative, statistically significant regression coefficient of the dummy ‘CS-User’ in the model iteration ‘RoA3’ and the dummy ‘CS-Empiric’ in iterations ‘RoA4’ and ‘RoA5’.

We conclude that MFIs that use credit scoring with poverty scoring have a lower return on assets than all other MFIs. This effect comes from the negative, statistically significant association between the use of credit scoring and RoA values in MFIs. It is impossible to determine the direction of causality on one hand. On the other hand, it is very unlikely that the use of credit scoring or credit rating, but credit scoring in particular, be the cause of lower-performing assets in MFIs. MFIs likely use credit scoring to address the issue of low asset profitability. Unfortunately, we have no reliable variable that would indicate the level of competition among MFIs in the country. We have no reliable variable that would indicate the level of indebtedness of micro-borrowers in each country. An MFI operating in a highly competitive market or in a market with significant client over-indebtedness levels would have to carefully select safe clients but also look into new markets involving relatively poorer clients. Credit scoring would help avoid the credit risk associated with smaller or overindebted clients. If such MFIs, forced by competition rather than pursuing a social mission, get to serve important numbers of financially excluded clients, it is worth for them to implement a poverty measurement technique. By proving to social investors, donors, and public authorities that they reach out to a large share of poor borrowers and that they have tools to control such downscaling in loan size to poorer borrowers, they could qualify for additional benefits in the form of cheaper funding, more funding at market rates when the MFI is already well leveraged, and other benefits. Such benefits might improve the profitability of the MFI, but since the market is saturated, such improvements still remain below the baseline.

6.5 The joint use of credit scoring and poverty scoring, and return on equity

The regression model iterations presented in Table 17 are a variation of the regression model ‘RoE1’ presented in Table 14. We add to that initial model variation, in several iterations, variables describing the use of credit scoring. As in the previous regression analysis, the variables describing the use of poverty scoring were included in the referenced model.

Table 17. The linear regression models explaining the variation in return on equity including through variables indicating the use of credit scoring and the use of poverty measurement tools

Row #	RoE (year = 2014)	Model RoE3		Model RoE4		Model RoE5	
		B	Sig.	B	Sig.	B	Sig.
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)
1	(Constant)	-0.107	0.679	-0.085	0.740	0.004	0.988
2	Size: $\ln(\text{borrowers})$	0.016	0.330	0.015	0.351	0.016	0.324
3	% individual lending	0.023	0.737	0.025	0.718	0.002	0.980
4	% female borrowers	0.266	0.045	0.266	0.046	0.267	0.048
5	Borrowers / loan officers	0.000	0.701	0.000	0.691	0.000	0.711
6	Deposits / loans	-0.056	0.579	-0.051	0.617	-0.029	0.772
7	Operating expense / assets	-2.113	0.000	-2.106	0.000	-2.086	0.000
8	Financial expense / assets	-2.689	0.001	-2.690	0.001	-2.699	0.001
9	Financial revenue / assets	1.711	0.001	1.702	0.001	1.628	0.001
10	Credit union	-0.016	0.871	-0.020	0.841	-0.044	0.651
11	NBFI	-0.074	0.389	-0.076	0.374	-0.073	0.403
12	NPO	-0.094	0.295	-0.099	0.264	-0.111	0.215
13	Rural bank	0.159	0.502	0.142	0.550	0.085	0.720
14	AVGLoanPPP	0.000	0.542	0.000	0.581	0.000	0.797
15	Per capita GDP (PPP \$)	0.000	0.822	0.000	0.837	0.000	0.967
16	Debt / equity	-0.012	0.000	-0.012	0.000	-0.012	0.000
17	PAR30	-0.120	0.624	-0.125	0.613	-0.141	0.571
18	Non-earning liquid assets / assets	-0.193	0.388	-0.198	0.378	-0.242	0.290
19	# non-financial goals	-0.008	0.544	-0.008	0.537	-0.006	0.627
20	PM-User	0.066	0.160	0.064	0.171		
21	CS-User	0.016	0.697				
22	CS-Empiric			-0.002	0.964	-0.006	0.888
23	PM-Empiric					-0.017	0.717
24	<i>Model significance</i>	<.001		<.001		<.001	
25	<i>R squared</i>	0.474		0.473		0.462	
26	<i>Adjusted R squared</i>	0.351		0.350		0.337	
27	<i>Degrees of freedom</i>	106		106		106	

We note that the regression coefficient of the variable ‘PM-User’ maintains its sign but loses statistical significance. This is probably due to the important reduction in the data points used in the current regression analysis. Our focus in this particular analysis is on the regression coefficients of variables ‘CS-User’, ‘CS-Empiric’, and the combination ‘CS-Empiric’-‘PM-Empiric’.

We conclude that the joint use of poverty scoring and credit scoring is not associated with increased RoE ratios in MFIs. From previous analysis, presented in Table 14, we know that the

use of a poverty measurement technique is associated with higher RoE values, all other things being equal. The type of poverty measurement tool did not matter.

The use of credit scoring, in addition to a poverty measurement technique, is not associated with an increase in RoE values.

6.6 Chapter conclusions

Based on the low incidence of MFIs in our data samples that utilise both credit scoring and poverty scoring, we argue that the joint use of these techniques is not widespread in microfinance.

MFIs that use both a poverty measurement tool and credit scoring tend to have greater outreach to poor borrowers. The regression coefficients show that the use of a poverty measurement tool in MFIs is associated with lower average loan balances, and the use of poverty scoring is also associated with lower average loan balances. However, only the association between the use of a poverty measurement tool and the proxy for social outreach is statistically significant. The association between poverty scoring and the same proxy did not reach statistical significance (0.179 instead of ≤ 0.1).

The fact that the use of credit scoring (and credit rating) is not associated with a decrease in the social outreach of MFIs is an encouraging finding. The lack of discord between the two scoring techniques when used together, with regard to MFIs' social mission, leaves room for synergies where possible. In fact, if the poverty and credit riskiness of micro-borrowers are modestly correlated, but also if this relationship is non-linear, at a certain level of outreach to poor borrowers, credit scoring might flag applicants experiencing extreme poverty as highly risky, thus slowing or halting the downscaling efforts of the MFI. An analysis of the correlation between poverty and credit risk could provide additional insights into possible synergies and conflicts when the two scoring techniques are used in credit markets affected by high poverty rates. Such an analysis would further reinforce the theoretical arguments developed in Section 1.6.4.

The joint use of credit scoring and poverty scoring is not associated with reduced financing or operating costs in MFIs. An MFI that can accurately estimate the credit risk of its loan

applicants should be more creditworthy than an MFI that does not use credit scoring. All other factors being equal, an MFI that uses credit scoring should qualify for cheaper financing as its risk is smaller. An MFI that uses poverty scoring should attract cheaper funding from social investors. An MFI that uses both credit scoring and poverty scoring should be able to blend its financing sources to obtain the cheapest funds available. However, regression analysis did not support this hypothesis. Additionally, the hypothesis that MFIs using both credit scoring and poverty scoring prefer to secure additional financing at market rates, when they are already highly leveraged, could not be substantiated. In fact, the hypothesis that MFIs using both scoring techniques are highly leveraged was also not proven.

The joint use of credit scoring and poverty scoring seems to have an antagonistic effect on the return on assets ratio of MFIs. In the previous chapter, we showed that the use of a poverty measurement tool is associated with an increase in RoA in MFIs, although the significance of the respective regression coefficient slightly exceeded the $P \leq 0.1$ threshold. The use of credit scoring, however, is associated with reduced RoA in MFIs. This association remains statistically significant and consistent across all regression iterations involving credit risk estimation tools in general, and credit scoring in particular. We conclude that MFIs that use both credit scoring and poverty scoring tend to register lower RoA values.

Finally, the joint use of credit scoring and poverty scoring is associated with higher return on equity in MFIs. In the previous chapter, we showed that the use of a poverty measurement tool is associated with higher RoE values. In this chapter, we show that the use of credit scoring has no statistically significant impact on RoE values. MFIs that use both a poverty measurement tool and credit scoring register higher RoE values, primarily due to the use of the poverty measurement tool in the MFIs.

We conclude the chapter by contrasting the findings on the association between the joint use of credit scoring and poverty scoring and the profitability metrics of MFIs. The use of a poverty measurement tool is associated with higher RoE values, both when controlling for the use of credit risk assessment tools and when not controlling for them. Conversely, the use of credit scoring (and credit rating) is associated with lower RoA values, whether or not we control for the use of poverty measurement tools. In summary, credit scoring (and credit rating) is linked

to lower profitability, whereas poverty scoring and other non-statistical poverty measurement tools are associated with higher profitability for MFIs.

We reaffirm the conclusion that the joint use of credit scoring and poverty scoring is associated with a ‘synergistic’ increase in the social outreach of MFIs. Further investigation into the relationship between poverty levels and credit risk at the micro-borrower level could provide additional insights into the limitations of credit scoring in supporting the downscaling efforts of MFIs when approaching extreme poverty levels, where credit risk might be high.

This conclusion is relevant for microfinance institutions and organisations providing services to poorer segments of the population that involve a credit component and thus the underlying credit risk. For instance, consider a small, private electricity company that exploits solar panels with storage capacity and sells electricity to neighbourhoods not connected to the central electrical grid. The company would be interested in enrolling as many new clients as it can sustainably handle to increase revenue and optimise costs. It might start promoting its services to wealthier households that could consume more electricity. However, equating perceived wealth with creditworthiness might be risky, as wealthier households may consume more but delay payments or refuse to pay, claiming inaccurate consumption estimates. Being wealthier, they may have their own generators running on gas or diesel, mitigating any impact from being disconnected from the new grid, except for the inconvenience of noise and refuelling. The company would thus be more invested in these business relationships, as it provided the cabling and consumption equipment, and might have to accept the delinquency of such clients.

On the other hand, poorer clients, who may not have the option of owning electricity generators and whose quality of life could improve significantly from the service, might be some of the best payers in the neighbourhood. To remain in business, the company would need credit scoring first. With credit scoring, it can prioritise the most creditworthy clients and then gradually connect less creditworthy ones, based on internal cost-control calculations. The electricity company may not need poverty scoring unless it lacks a reliable credit scoring tool and knows that poverty in the neighbourhood is strongly correlated with good payment behaviour. However, such an assumption could pose risks, as the poorest households might not

be able to pay for electricity or might use so little that the company's investment in connection infrastructure becomes unprofitable.

The company may need poverty scoring if regional or central authorities decide to provide a subsidy for each connected poor household. The joint use of credit scoring and poverty scoring would help the company cluster its potential clients into (same) groups: 'wealthy & creditworthy', 'wealthy & credit risky', 'poor & creditworthy', and 'poor & risky'. The company would likely prioritise services to the two 'creditworthy' clusters. It could also create an internal subsidisation scheme for 'poor & risky' clients if the government subsidy is important or if electrification of the poorest households receives special attention from authorities and the press.

A similar case could involve a company providing housing to mid- and low-income families, allowing them to buy in instalments the real estate directly from the company. Even though lower-income families may be more willing to pay their instalments on time to retain and use the only real estate they have access to, the company would not need poverty scoring. They would only require credit scoring. However, the company might need to assess the poverty levels of its prospects and clients if certain stakeholders offer benefits either directly to poor clients in a way that benefits the company or directly to the company itself.

Organisations providing non-credit-related services to poorer segments of the population do not require credit scoring. Organisations providing credit-related services to these populations do not require poverty scoring unless they can benefit from collecting data on the share of poor clients served, their average poverty level, and their recorded progress out of poverty.

One scoring tool can only substitute the other if poverty and creditworthiness are strongly and consistently correlated with each other. We explore this question further in the next chapter.

Chapter 7 The joint use of credit scoring and poverty scoring – a client level perspective

A strong negative correlation between poverty and creditworthiness would render the joint use of poverty scoring and credit scoring redundant. If a borrower's poverty level can accurately predict her creditworthiness – higher poverty levels indicate higher probabilities of default – then combining these two scoring techniques would be unnecessary, as one could replace the other. In such a scenario, borrowers would be grouped into several clusters: 'poor & not creditworthy', 'not poor & creditworthy', and potentially a cluster of borrowers with average poverty and credit risk. In this scenario, there would be no clusters of poor and creditworthy borrowers, which underpins the entire microfinance movement.

7.1 Introduction

This chapter examines whether and to what extent poverty and creditworthiness are correlated using real MFI data. Our hypothesis is that there is a small negative correlation between poverty and creditworthiness. This correlation can be explained by the fact that poor borrowers often lack material possessions that could act as a safety net in the event of business or household emergencies. For example, if two otherwise identical shopkeepers who borrowed money to purchase merchandise are forced to close their businesses due to a new supermarket opening nearby, the shopkeeper with a car – the wealthier of the two – can sell the car or use it as collateral to borrow additional funds to repay the defaulting loan and potentially relocate the shop. In contrast, the borrower without a car is more likely to default on the loan or face severe delinquencies. Given that such business disruptions are relatively rare and both the microfinance institution and borrowers expect normal conditions, most microloans are repaid on time when the credit transaction aligns with the borrower's needs and repayment capacity.

Poverty is a major cause of financial exclusion. Financial exclusion reinforces the vicious cycle of poverty, as poor households cannot access financial services, including credit, to improve their circumstances through entrepreneurship or education. Financial inclusion helps break this cycle by removing barriers to investment in income-improvement and income-generating activities like education and entrepreneurship. If the correlation between poverty and credit riskiness is weak or insignificant, it raises the question: why do poor people lack access to mainstream credit? Potential reasons include: banks not having cost-effective methods to assess poor borrowers' creditworthiness, avoiding low-income segments for reputational reasons, or

finding the potential returns from serving low-income populations insignificant. Additionally, demand for financing from poorer segments may be low due to self-exclusion – potential low-income borrowers might find it difficult to navigate complex contractual language, procedures, and calculations involved in mainstream financial services. Poor potential borrowers might also avoid banks if they perceive them as costly due to operational fees. Banks typically offer bundled services like current accounts, payment cards, and online banking, with monthly fees that can be waived for high transaction volumes. For poorer clients, these fees can be seen as excessive and wasteful, especially if most of the bundled services are rarely used.

Microfinance institutions address self-exclusion by positioning themselves as service providers for less wealthy individuals. Their proactive approach, including sending loan officers to markets and streets where self-employed and microbusinesses operate, helps reduce self-exclusion. Opening branches in low-income neighbourhoods and employing local staff further removes subjective barriers for poor entrepreneurs seeking formal financial services.

Donors and social investors support MFIs with equity, grants, and low-interest loans, believing that financial inclusion can sustainably lift certain groups out of poverty. This support helps MFIs scale up while targeting underserved market segments. As poor individuals improve their income, the entire community benefits from positive spillovers, justifying ongoing subsidies to MFIs committed to serving the poor. However, since subsidies are limited in developing countries, donors and social investors may require MFIs to focus predominantly on the poor to receive support. Poverty scoring is not only a way to demonstrate to stakeholders that an MFI serves the poor but also a tool to guide outreach efforts. While poverty scoring can help identify poor borrowers, it can also introduce errors: type I errors (false positives) where a borrower is wrongly identified as poor, and type II errors (false negatives) where a poor borrower is wrongly identified as not poor. Using poverty scoring as a strategic tool to increase the share of poor borrowers by directing MFI outreach efforts to regions and segments with poorer populations can be more effective than relying solely on poverty scores to deny credit to applicants with high poverty scores (low probability of being poor). Some loan applicants may still experience poverty despite high poverty scores, as no poverty scoring algorithm is perfect.

If MFIs move away from serving low-income clients, they risk abandoning their social mission and competing with mainstream financial institutions. Banks, for example, are better equipped

to serve borderline clients – those at the higher end of the micro-borrower spectrum who have already demonstrated good repayment behaviour when dealing with MFIs. By focussing on low-income entrepreneurs and households overlooked by banks, MFIs can build resilience necessary for growth. Credit scoring should help these MFIs avoid high credit risk. If poverty and creditworthiness are weakly correlated, MFIs will also need poverty scoring to prevent mission drift.

7.2 Data and methodology

A sample approaching 800 real loans issued by a microfinance institution from the Eastern Mediterranean were used as main data for the analysis presented in this chapter. These loans were issued to microentrepreneurs engaged in basic agricultural activities. The MFI received some subsidised funds to support these microentrepreneurs who were experiencing financial exclusion.

Although the sample was anonymised, the profiles of the loans, their repayment behaviour, as well as the characteristics required to estimate the likelihood that the borrower's household consumption is below the poverty line were available. Loans were issued from 2019 to mid-2022. The loan amounts ranged from 100 to 500 local currency units, which is 0.33 to 1.65 of the GDP per capita in the country. The average loan was 175 local currency units, which is less of 0.60 of the GDP per capita. Loan term ranged from 12 to 56 months with the average of 34 months.

The likelihood of poverty – consumption below a set poverty line – was estimated using the Simple Poverty Scorecard® developed for the country (Innovations for Poverty Action, 2024), using extensive data collected during a nation-wide, government-led household income and expenditure survey.

The country-specific Simple Poverty Scorecard® is an indirect poverty measurement tool centred on a poverty scoring algorithm using a poverty scorecard with ten indicators. Collection of these ten indicators by a loan officer is supposed to be quick and inexpensive, although it requires a visit to the home of the loan applicant, which is a common practice in microfinance. These ten indicators are collected by finding the accurate answers to the following ten questions:

1. How many members does the household have?
2. How many household members worked at least one hour in the past week?
3. Does any household member work as a legislator, senior official, manager, professional, technician, or associated professional?
4. How many rooms, not counting the kitchen, does the residence of the household have?
5. Does the household own a combined gas stove with oven?
6. Does the household own a vacuum cleaner?
7. Does the household own an air conditioner?
8. Does the household have a computer connected to the internet?
9. How many landlines and mobile telephones does the household have?
10. Does the household own a private car?

Using the poverty scoring algorithm yields a poverty score which ranges from 0 – highest probability of the applicant having consumption below the poverty line to 100 – lowest probability of the applicant being poor. The chosen poverty line is four times the World Bank’s extreme poverty line. At that time the international extreme poverty line was 1.90 US dollars per person per day using 2011 purchasing power parity (Ferreira *et al.*, 2015). The international extreme poverty line is described in detail in Chapter 5.

The repayment behaviour of microloans allowed to identify a sample of ‘good credit risks’ – loans repaid correctly with no delinquency superior to 30 calendar days, and ‘bad credit risks’ – loans which registered delinquencies greater than 30 calendar days. Thirty days past due in microfinance is considered a severe delinquency after which it is difficult for the borrower to recover. After 30 calendar days being late, the next loan instalment becomes due. The borrower needs thus to repay two instalments and the penalty for failing to repay the overdue instalment on time.

Because the repayment of some loans happened during the active phase of the Covid-19 pandemic, loans which registered severe delinquencies in the period March-December 2020 were not included in the initial data sample.

The profiles of selected loans allowed the creation of a statistical credit scoring algorithm using the conceptual framework developed and presented in section 2.8. Table 18 presents an example of how characteristics have been selected to be included in the credit scoring algorithm. It also presents the number of good (584) and bad (189) credit risks (transactions) in the entire sample and the percentage of bad credit risks in this sample (24.5 percent). In order to identify within available variables, the characteristics of loan transactions which have potential credit risk discrimination power, we compare the bad rate ‘% bad’ of each characteristic with the bad rate of the sample. Characteristics which register relatively higher bad rates are potentially predictors of bad credit risks, while characteristics which register relatively lower bad rates are potentially predictors of good credit risks.

In fact, the comparison of bad rates within variables are more relevant. Loan applicants who are men in our sample, as presented in Table 18, have a bad rate almost 5 times higher than that of women. A dummy variable, ‘Is woman’, will be created to identify female loan applicants. This variable will be included in the logistic regression analysis to determine its isolated contribution to the probability of a loan transaction being a good credit risk. By including in the logistic regression analysis only characteristics of a variable which register a bad rate smaller than the characteristic with the worst bad rate, one achieves a credit scoring algorithm which initially assigns a bad credit score to all foreseen credit transactions. Once the algorithm identifies characteristics statistically associated with good credit risks, it adds corresponding points (scores) that gradually improve the final credit score. In this way, a potentially good credit transaction will receive a good credit score, which is above the cut-off score for bad credit risks.

If being a woman is associated with lower credit risk in the analysed database, the regression coefficient and its statistical significance will validate this, allowing loan officers who use the resulting credit scoring algorithm to avoid gender bias. It could be, however, that only men are involved in certain vital, yet high-risk agricultural activities, such as raising flocks of ruminant animals that are constantly at risk of predator attacks. In such cases, the risk is associated with the activity itself, rather than the gender of the entrepreneur. It is a different point, from a sociological angle, that women being associated with lower credit risk and men with higher credit risk because of men being involved in high-risk agricultural activities is itself a sign of

gender bias in society. A well-designed credit scoring algorithm would account for these nuances, enabling unbiased credit decisions.

Table 18. Example of characteristics of the loan transactions selected for logistic regression analysis required to elaborate the credit scoring algorithm

required to elaborate the credit scoring algorithm							
Type of credit risk		Good	Bad	TOTAL	% bad	Distribution	Regression dummy
Variable	TOTAL	584	189	773	24.5%	100%	
Gender of applicant							
Characteristic	Man	548	187	735	25.4%	95%	x
Characteristic	Woman	36	2	38	5.3%	5%	Is woman
Age of the applicant at loan application (years, rounded)							
Characteristic	18 – 25	60	37	97	38.1%	13%	x
Characteristic	25 – 30	95	43	138	31.2%	18%	Is 25-30 years
Characteristic	30 – 35	182	57	239	23.8%	31%	Is 30-35 years
Characteristic	35 – 50	185	34	219	15.5%	28%	Is 35-50 years
Characteristic	50 – 65	62	18	80	22.5%	10%	Is 50-65 years

In the case of age, as presented in Table 18, the riskiest category is 18-25 years – young entrepreneurs are generally riskier because of lack of experience and lower stability in both their personal and professional lives. A dummy coding for this age interval will not be created. All other age segments will be coded and included in the logistic regression analysis. One can notice the linear relationship between age and credit risk: as age increases, the bad rate decreases. This until we reach the age bracket of 50-65 years. This case illustrates why most variables need to be segmented and converted into dummy variables for multivariate statistical analysis using linear or logistic regression. Linear and logistic regression models assume a linear relationship between the predictors and the outcome variable (the log-odds of the outcome in the case of logistic regression). In practice, this assumption may hold true only for certain segments of the predictors.

It is worth noting that a credit scoring algorithm should be developed on a training sample and tested on a test sample.

The developed credit scoring algorithm, when used, yields credit scores ranging from 0 – highest probability of ‘bad’ credit behaviour to 100 – lowest probability of ‘bad’ credit behaviour and default. A scale of 0 to 100 was preferred to the classical scale 0 to 1000 to match the poverty scoring scale.

For each microloan, a credit score and a poverty score can be calculated. These combinations of scores, but also true good and bad credit risk classes, are used to calculate correlations and create a matrix in line with the proposal made in section 1.6. Observing the correlation coefficients and how loans are distributed in the matrix helps determine how strongly poverty and creditworthiness are correlated. Such observations can help understand if a management tool based on the joint use of credit scoring and poverty scoring can help the MFI in practice, not in theory, remain both sustainable and committed to its social mission.

Our hypothesis is that poverty and credit riskiness are modestly correlated. However, a high correlation between poverty and credit riskiness – observable only at higher poverty levels – could explain the lack of a clear, statistically significant relationship between credit scoring and the average loan balance per borrower in MFIs (observed in section 6.2). The average loan balance serves as a proxy for outreach to poorer borrowers. If the poverty level of loan applicants reaches a point where it strongly correlates with credit riskiness, credit scoring may prevent these clients from obtaining loans. This, in turn, could hinder or slow the MFI's efforts to downscale, which is to reach borrowers who need relatively smaller loans.

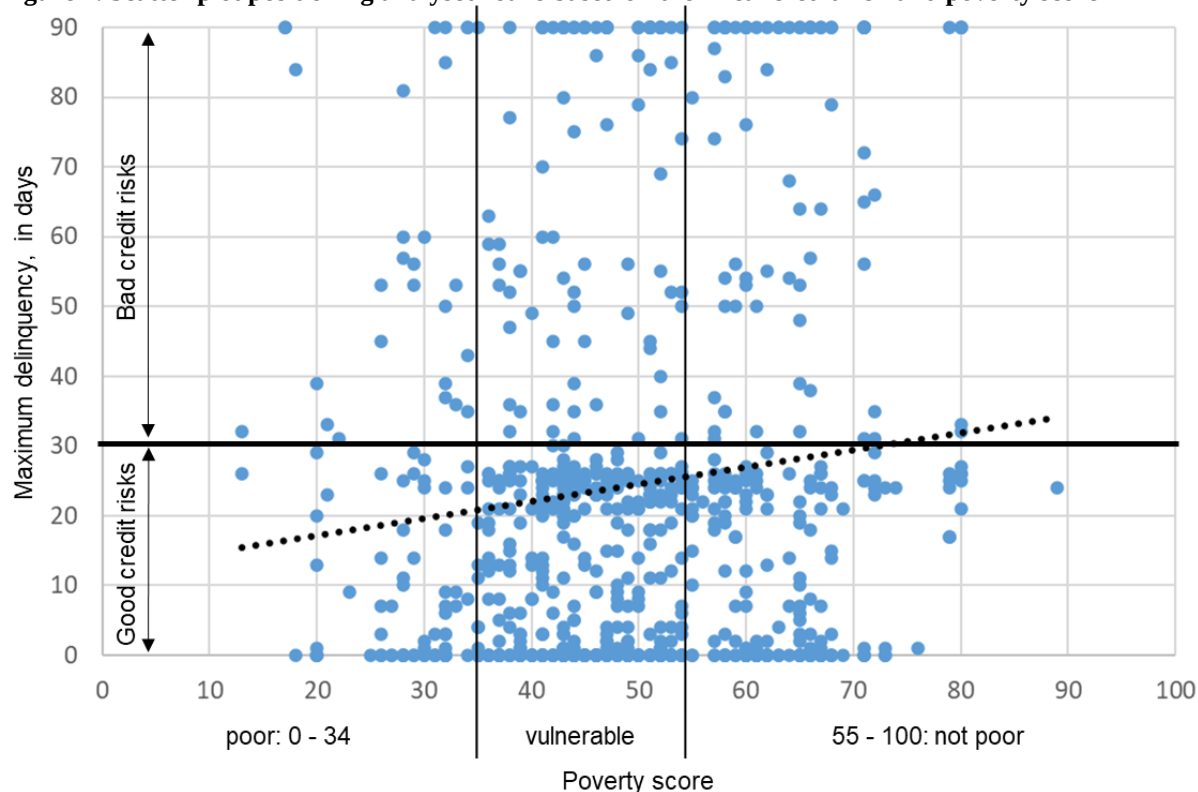
7.3 Findings

Figure 4 presents the distribution of analysed loans across two axes: credit risk and poverty level. Credit risk is represented through the maximum number of days the loan was past due. For loans with severe delinquencies, the counter of days past due stopped at 90 consecutive days. All loans which registered a repayment delinquency greater than 30 days (24.5 percent) were considered bad credit risks. Poverty level was represented through the poverty score. We considered the poverty score as a better estimation of the real poverty level of the borrowers than household income, as estimated by loan officers.

It has been observed that loan officers estimate household revenue mainly based on business revenues, business expenses and household revenues from other sources. Household expenses are either ignored or underestimated, despite their significant share in overall expenses, especially in poorer households. The loan deal is structured around the disposable income, which is greatly overestimated for families with members requiring care, such as small children and the elderly.

Despite operating in an environment where households are typically large and multi-generational, often combining older parents, sons, and their families, the loan application form of the respective MFI lacks the necessary fields to collect information about household members. This omission includes details about their capacity to generate additional income or, conversely, their need for care from other members.

Figure 4. Scatter plot positioning analysed loans based on their real credit risk and poverty score



In Figure 4 one can notice how good credit risks (75.5 percent) also tend to register delinquencies, but these do not cross the 30 days past due threshold, in spite of approaching it closely in many cases. Some good credit risks, including those with high probability of being poor, register perfect repayment behaviour, without a single delinquency. One can notice the absence of borrowers with very high probability of experiencing poverty (poverty score below 20) and also very low probability of poverty (poverty score above 80) – a sign that the MFI serves a range of clients which are neither too poor nor wealthy.

7.3.1 Correlations

In our sample, as the dotted trendline in Figure 4 indicates, credit risk and poverty level are modestly correlated. Table 19 presents the correlation results of relevant variables. The

resulting Pearson correlation coefficient (r) between the poverty score and the maximum number of days past due is 0.12 (column 3, row 15). This coefficient is statistically significant at $P < 0.001$ level (column 3, row 16). This indicates a very weak positive linear relationship between poverty and creditworthiness. As the probability of experiencing poverty increases, the probability of default slightly decreases. This is counterintuitive, disproving the hypothesis, which anticipated a negative correlation coefficient. In other words, poorer borrowers exhibit slightly better credit behaviour than their wealthier peers. This observation cannot be explained by significantly lower loan amounts or lower monthly instalments that relatively poorer borrowers get and then easily repay. Credit amounts (see correlation coefficient in column 6, row 15) and monthly instalments (column 7, row 15) do not correlate with the poverty scores of borrowers. One explanation why poorer borrowers repay their loans slightly better than less poor borrowers could be the fear of losing their reputation as a good borrower. In the absence of material possessions, reputation as disciplined client could be one of the most important assets a poor borrower might have.

Table 19. Correlation results between the credit score and the poverty score as well as some variables associated with these scores

Row	Variable	<i>r</i> , P	Max days	DI	DI / pers.	Loan am.	Loan inst.	Credit score
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	Is bad credit risk	<i>r</i>	0.64	-0.06	0.02	-0.12	-0.13	-0.37
2		P	0.000	0.108	0.624	0.001	0.000	0.000
3	Maximum days past due (Max days)	<i>r</i>	1	-0.07	0.01	-0.09	-0.11	-0.26
4		P		0.053	0.719	0.012	0.001	0.000
5	Disposable income (DI)	<i>r</i>	-0.07	1	0.29	0.21	0.35	0.07
6		P	0.053		0.000	0.000	0.000	0.040
7	Disposable income / person (DI / pers.)	<i>r</i>	0.01	0.29	1	0.04	0.19	-0.19
8		P	0.719	0.000		0.285	0.000	0.000
9	Loan amount (Loan am.)	<i>r</i>	-0.09	0.21	0.04	1	0.77	0.17
10		P	0.012	0.000	0.285		0.000	0.000
11	Loan instalment (Loan inst.)	<i>r</i>	-0.11	0.35	0.19	0.77	1	0.08
12		P	0.001	0.000	0.000	0.000		0.033
13	Credit score	<i>r</i>	-0.26	0.07	-0.19	0.17	0.08	1
14		P	0.000	0.040	0.000	0.000	0.033	
15	Poverty score	<i>r</i>	0.12	-0.03	0.23	0.02	-0.02	-0.21
16		P	0.001	0.336	0.000	0.611	0.599	0.000
17	Poverty score (lowest third –poorest)	<i>r</i>	0.01	-0.03	0.04	-0.11	-0.08	0.17
18		P	0.867	0.584	0.536	0.073	0.176	0.005
19	Poverty score (middle third)	<i>r</i>	0.05	-0.13	-0.11	-0.05	-0.07	-0.06
20		P	0.417	0.038	0.089	0.469	0.255	0.348
21	Poverty score (highest third – least poor)	<i>r</i>	0.04	0.22	0.24	0.02	0.05	-0.26
22		P	0.549	0.001	0.000	0.693	0.453	0.000

Abbreviations: *r* – coefficient of Pearson correlation; P – significance level (2-tailed)

We go a step further. Rows 17 to 22 in Table 19 repeat the correlation analysis for the variable ‘Poverty score,’ but this time the variable is divided into terciles – a division of the ascending distribution of poverty scores into three parts equal by number of cases. Each tercile is then correlated with all other variables in Table 19. This approach helps to determine whether the relatively small and negative correlation between poverty scores and credit scores is consistent across different segments of the distribution of poverty scores.

We find in the lower tercile, which concentrates the third of loans with the lowest poverty scores (highest probability of being poor), that poverty scores and credit scores correlate positively ($r = 0.17$, $P < 0.01$, refer to column 8, rows 17 and 18 of Table 19). This is the exact opposite finding when we compare with the correlation coefficient of the entire distribution of poverty scores (refer to column 8, rows 15 and 16 of Table 19). It is also the opposite of the correlation coefficient of the higher tercile, which concentrates the third of loans with the highest poverty scores (highest probability of being not poor), as shown in column 8, rows 21

and 22 in Table 19. Such a finding actually supports the hypothesis that poverty and credit riskiness are moderately and positively correlated, but this is true only for the third of loans with the lowest poverty score (highest probability of poverty) in our sample.

It is noteworthy that there is a positive yet modest correlation ($r = 0.23$, $P < 0.001$) between the calculated disposable income per household member and poverty scores (refer to column 5, row 15 of Table 19). This observation indicates that loan officers may systematically overestimate the repayment capacity of borrowers who are more likely to experience poverty. From a financial inclusion perspective, this overestimation might counteract an MFI's conservative approach to loan amounts. If the MFI uses a conservative ratio of loan instalment to disposable monthly income, leading to insufficient loan amounts, an overestimation of disposable income could result in larger loans and potentially greater financial inclusion impact, provided that the borrower can repay the loan and use it effectively to grow or sustain her income-generating activity. This situation further validates the importance of poverty scoring. Determining a household's actual disposable income is challenging for loan officers. On one hand, applicants often inflate their revenue and minimise their expenses to secure larger loans. On the other hand, loan officers lack the necessary information and techniques to accurately assess the impact of household composition on disposable income. While operating with imprecise estimates might occasionally benefit poorer borrowers, improving accuracy is crucial for sustainable financial inclusion.

7.3.2 Poverty scorecard variables with credit risk prediction power

The credit scores in the analysis presented in this chapter have been calculated using a credit scoring algorithm, which has been developed using the sample data. The Simple Poverty Scorecard variables (Innovations for Poverty Action, 2024) required for poverty scoring calculations were initially not incorporated into the development of the credit scoring algorithm intended to calculate the probability of default of the loans in the data sample. Prior to implementing poverty scoring, the MFI collected a limited set of poverty-related variables, such as the number of household members, but did not differentiate by age or capacity of these members to work. These pre-existing variables were not excluded from the initial regression analysis. The initial credit scoring algorithm produced an area under the receiver operating characteristic (ROC) curve of 0.72, indicating significant credit risk discrimination power.

A new credit scoring algorithm was subsequently developed by including the additional variables collected for poverty scoring, which demonstrated certain credit risk discrimination power. The updated (final) credit scorecard achieved an area under the ROC curve of 0.74, reflecting a slight improvement in credit risk discrimination compared to the initial algorithm. An ideal credit scorecard that perfectly classifies all good and bad credit risks would have an area under the ROC curve of 1.

From the list of ten variables composing the poverty scorecard, four revealed to have certain credit risk discrimination power. These are presented in Table 20. For each characteristic of the presented variables, we present the poverty points (poverty scores) it adds to the total poverty score. The higher the points, the bigger the contribution to the total poverty score. The higher the total poverty score, the higher the probability that the assessed subject is not poor.

Table 20. Characteristics from the poverty scorecard which have credit risk discrimination power

Row	Type of credit risk		Good	Bad	TOTAL	% bad	Distrib.	Associ- ation	Poverty points
	Variable	TOTAL	584	189	773	24.5%	100%		
(0)	Column: (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	Household members: How many members does the household have?								
2	Characteristic	1 – 2	77	34	111	30.6%	14%	Positive	38
3	Characteristic	3	84	35	119	29.4%	15%	Positive	30
4	Characteristic	4	97	34	131	26.0%	17%	Positive	23
5	Characteristic	5	102	30	132	22.7%	17%	Positive	15
6	Characteristic	6	96	21	117	17.9%	15%	Positive	13
7	Characteristic	7	71	12	83	14.5%	11%	Positive	7
8	Characteristic	8	29	12	41	29.3%	5%	Negative	4
9	Characteristic	9 +	28	11	39	28.2%	5%	Negative	0
10	Household workers: How many household members worked at least one hour in the past week?								
11	Characteristic	0	58	35	93	37.6%	12%	Negative	0
12	Characteristic	1	234	70	304	23.0%	39%	Negative	1
13	Characteristic	2	188	53	241	22.0%	31%		2
14	Characteristic	3 +	104	31	135	23.0%	17%		3
15	Air conditioner: Does the household own an air conditioner?								
16	Characteristic	No	492	150	642	23.4%	83%	Negative	0
17	Characteristic	Yes	92	39	131	29.8%	17%		5
18	Rooms: How many rooms, not counting the kitchen, does the residence of the household have?								
19	Characteristic	1 – 2	6	2	8	25.0%	1%		0
20	Characteristic	3	261	121	382	31.7%	49%	Negative	6
21	Characteristic	4	221	50	271	18.5%	35%	Positive	7
22	Characteristic	5 +	96	16	112	14.3%	14%	Positive	14

The characteristic '1-2' in the variable 'Household members' has the highest poverty points (38) of all variables and their characteristics presented in Table 20 (refer to column 9, row 2). It means that if a household has one or two members, it is less poor than the households with more members, all other things being equal. The same characteristic '1-2' in the variable 'Household members' which make the household less poor, makes the household riskier, credit-wise, as the '% bad' for this characteristic (30.6 percent, refer to column 6, row 2) is much higher than the bad rate of the sample, which is 24.5 percent. In this case a lower probability of experiencing poverty is associated with a higher probability of default. The figure in column 8, row 2 in Table 20 captures this counterintuitive 'positive' association between probability of default and probability of not being poor. For the variable 'Household members' the positive association between probability of default and probability of not experiencing poverty is not valid for the last two segments, where the association is negative (refer to column 8, rows 8 and 9). In these last two segments poverty increases together with the probability of default. Household with eight or more members have the highest probability of being poor, but also one of the highest probabilities of default – if compared with all other characteristics of the variable 'Household members'.

Another case when chances of not being poor increase with the chances of default, is in households with air conditioning (column 8, rows 16 and 17 of Table 20). Having air conditioning increases the total poverty score and with it the probability of the household not being poor. Having air conditioning is associated with higher credit risk.

Households with more than four living rooms appear both: less poor and less risky, credit wise. The positive association is indicated in column 8, rows 21 and 22 of Table 20.

The above examples reveal that the relationship between poverty and credit risk is complex and multifaceted. Factors such as household size, amenities, and living conditions can exhibit varying effects on poverty and credit risk. Specifically, while some indicators suggest a direct correlation between reduced poverty and increased default risk, others demonstrate a nuanced interplay where increased poverty is associated with heightened credit risk. These findings underscore the importance of considering multiple variables and their interactions when assessing credit risk and poverty.

Relying on imprecise estimates of disposable income is not a sustainable strategy for calculating the loan amount and the credit risk of the foreseen loan transaction. Investing in better tools and methods to calculate incomes more accurately is essential for improving financial inclusion and risk management. However, it is important to recognise that as the accuracy of income calculations improves, applicants may also become more sophisticated in presenting inflated income figures. Therefore, while enhancing the accuracy of income assessments is crucial, it must be complemented by robust verification processes to prevent manipulation and ensure the reliability of the financial evaluation.

7.3.3 Loan distribution across poverty-credit risk clusters

Knowing the probability of bad credit behaviour for each loan and the probability of the borrower to be poor, we construct a matrix in line with the proposal from section 1.6. Table 21 presents the distribution of loans by credit score and poverty score in a 3 x 3 matrix setting.

Two cut-offs have been used for poverty scoring and two for credit scoring. For poverty scoring, these two cut-offs created three intervals. The interval [0-34] called ‘poor’ concentrated borrowers with a probability of 71.7 percent of being poor, based on data used to create the poverty scorecard (Innovations for Poverty Action, 2024). The following interval (34-54] called ‘vulnerable’ concentrated borrowers with a probability of being poor of 23.4 percent. The last interval (54-100] called ‘not poor’ concentrated borrowers with a probability of being poor of 8.4 percent.

For credit scoring, the selected two cut-offs created also three intervals. The first interval [0-34] called ‘risky’ concentrated borrowers with a probability of bad credit behaviour of 70.0 percent, based on our sample. The interval (34-86] called ‘average’ concentrated borrowers with a probability of bad credit behaviour of 30.5 percent. The last interval (86-100] called ‘safe’ included borrowers with a probability of bad credit behaviour of 7.0 percent.

Table 21. Distribution of loans by credit score and poverty score

Number of loans per cluster and respective percentages. Σ (loans) = 773; Σ (percentages) = 100 percent.			Poverty score range and range name		
			[0 – 34]	(34 – 54]	(54 – 100]
			Poor	Vulnerable	Not poor
Credit score range and name of range	[0 – 34]	Risky	-	1 (0.1%)	9 (1.2%)
	(34 – 86]	Average	72 (9.3%)	292 (37.8%)	180 (23.3%)
	(86 – 100]	Safe	20 (2.6%)	144 (18.6%)	55 (7.1%)

Table 21 reveals the low share of estimated ‘risky’ loans: 10 credit transactions representing 1.3 percent of total loans in the sample. This means that the MFI managed to identify relatively well the very bad credit risks. We do not know how many ‘risky’ transactions have been refused by the loan officers, but the low incidence of estimated ‘risky’ loans is a positive factor for the credit risk function in the MFI. In fact, Table 22 reveals that out of the 10 credit risk transactions which were estimated as ‘risky’ only seven were truly risky, while the remaining 3 were good credit risks. Table 22 presents the number of truly good credit risks in each cluster separated by a semicolon from the number of truly bad credit risks in the cluster. The bad rate (% truly bad) in each cluster is presented in brackets.

Table 22. Number of good and bad credit risks, and bad rate in each cluster

Number of true good loans; number of true ‘bad’ loans per cluster. Cluster’s bad rate. Σ (good loans) = 586; Σ (bad loans) = 187.			Poverty score range and range name		
			[0 – 34]	(34 – 54]	(54 – 100]
			Poor	Vulnerable	Not poor
Credit score range and name of range	[0 – 34]	Risky	-	1; 0 (0%)	2; 7 (78%)
	(34 – 86]	Average	46; 26 (36%)	216; 76 (26%)	117; 63 (35%)
	(86 – 100]	Safe	19; 1 (5%)	135; 9 (6%)	50; 5 (9%)

It is noticeable that all seven true bad credit risks classified as ‘risky’ by credit scoring are from the ‘not poor’ category, as classified by poverty scoring. This suggests that relative wealth may lead loan officers to mistakenly view it as a sign of creditworthiness. In fact, when comparing ‘vulnerable’ and ‘not poor’ clusters pairwise, the bad rate in ‘not poor’ clusters is higher than in ‘vulnerable’ (poorer) clusters within the same credit score range.

One can observe in Table 21 that 7.1 percent of loans are classified ‘not poor’ based on one axis and ‘safe’ based on the other. Table 22 shows that the real bad rate in the cluster ‘not poor & safe’ is 9 percent, significantly lower than the 24.5 percent bad rate in the sample. Mainstream financial institutions could try to poach such borrowers from the MFIs and their low number (only 55 loans in 773) is a possible confirmation that the MFI is under such pressure.

Some clients of the MFIs prefer to stay with the MFI even when they become bankable. Continuing to serve these clients is not mission drift (Armendariz and Szafarz, 2011). The eventual extra profits such borrowers generate for the MFI can be used to subsidise lending to riskier borrowers which are poorer.

The largest cluster in the sample is ‘vulnerable & average credit risk’. It gathers 37.8 percent of all loans. The ‘bad rate’ in this cluster is 26 percent, which is close to the sample ‘bad rate’ (24.5 percent). About one in four borrowers in the cluster experienced bad credit behaviour, making the loan a bad credit risk.

Borrowers in all three ‘poor’ clusters represent only 11.9 percent or 92 loans. None of these loans are ‘risky’ and only 20 (2.6 percent of total loans) are estimated as ‘safe’. In the ‘poor & safe’ cluster out of the 20 loans, 19 are true good credit risks. This finding confirms the existence of ‘poor & safe’ borrowers. However, they are less than three people in 100 in our sample. All other ‘poor’ borrowers are concentrated in the ‘average credit risk’ category.

7.4 Chapter conclusions

In this chapter, using real MFI data, we demonstrate the existence of ‘poor & safe’ borrowers – the ideal clients for MFIs from a double bottom-line perspective. ‘Poor & safe’ borrowers are a minority in our sample, and the question of whether such borrowers are rare in the market, or whether the respective MFI simply avoided most ‘poor’ loan applicants, including those who are ‘safe’ (due to the lack of credit scoring), remains unanswered. Few loans were classified as ‘not poor & risky’. Serving these would not advance either the social agenda of the MFI or its financial sustainability. We did not find ‘poor & risky’ borrowers. Loan officers would have sufficient motives to reject loan applications that fall under the ‘poor & risky’ cluster, especially if they are biased against poorer loan applicants. We have shown that in the poorest third of the analysed micro-borrowers, poverty and credit risk are mildly positively correlated. This correlation was expected, as material possessions can serve as a safety net in case of emergencies or issues with loan repayment. If loan officers notice such a correlation, it could reinforce eventual bias against poorer borrowers, which credit scoring could help mitigate.

‘Vulnerable & average credit risk’ borrowers constitute the largest cluster in our sample. This highlights the challenge MFIs face. MFIs need credit scoring to rank loan applicants with average credit risk by credit score. Such ranking would allow the MFI to have different underwriting approaches for those with relatively higher and lower credit risks. From a financial perspective, it could be reasonable to reject all loan applicants from the ‘risky’ clusters, as well as some applicants from the ‘average’ credit risk clusters – particularly those with the lowest credit scores. If the to-be-rejected applicants are from the ‘poor’ clusters, the MFI might decide to offer them specially designed small loans that give them access to finance while controlling credit risk and potential losses, or simply group loans. Such individual or group loans might not be profitable and would likely require external subsidisation. Any extra profits made from ‘not poor & safe’ borrowers could be used to subsidise these poorer, riskier borrowers. If careful financial inclusion helps the poorest entrepreneurs grow and become financially literate, the MFI can, in turn, ‘grow’ or ‘graduate’ its future core safe clients. As we have shown, among the poorest borrowers, credit risk decreases when poverty levels decrease.

We have shown that ‘poor & safe’ borrowers exist. We also demonstrated that ‘not poor & safe’ borrowers exist. Since these two clusters are likely not the majority in most MFIs, and since not many MFIs can implement client ‘graduation’ schemes on their own, support from donors and social investors is essential for advancing financial inclusion for ‘vulnerable’ (poorer) borrowers who are riskier. The use of poverty scoring in these MFIs could serve as a key indicator for these organisations when deciding which MFIs to collaborate with. The joint use of credit scoring and poverty scoring would be an even more compelling indicator if these organisations were aware of the benefits of the combined scoring technique. The joint use of credit scoring and poverty scoring would also inform MFIs on the level of subsidisation for poorer clusters they can themselves ensure.

We observed that in pairwise comparisons of the ‘vulnerable’ and ‘not poor’ clusters, the ‘bad rate’ in the ‘not poor’ clusters is higher than in the ‘vulnerable’ (poorer) clusters within the same credit score range. It is clear that wealth leads loan officers to mistakenly view it as a sign of creditworthiness. To avoid such costly biases, credit scoring is essential.

We find that poverty and credit risk are weakly negatively correlated among the wealthiest third of micro-borrowers in our sample – when their poverty increases, their credit risk

decreases. This result is counterintuitive, as we expected a positive, preferably weak, correlation across the entire distribution. We also find that poverty and credit risk are weakly positively correlated among the poorest third of micro-borrowers in our sample – when their poverty decreases, their credit risk decreases. We theorise that relatively poorer borrowers within the wealthiest third, as well as wealthier borrowers within the poorest third, may place significant value on their reputation as reliable borrowers. They might view this reputation as a critical asset, compensating for the lack of important material possessions that could otherwise signal creditworthiness to loan officers. In contrast, this dynamic does not apply to the poorest borrowers within the poorest third, who lack material possessions to safeguard their reputation in the face of unforeseen circumstances and thus cannot leverage their reputation as effectively. This dynamic also does not apply to the wealthiest clients within the wealthiest third. These could be borderline clients, whom banks can theoretically finance but avoid extending new or additional credit due to over-indebtedness or private knowledge of past bad credit behaviour.

Modern literature has not investigated the relationship between poverty and creditworthiness in such depth. Our analysis provides an interesting perspective, revealing the non-linear relationship between poverty and credit risk. Practitioners generally view this relationship as linear and positive, both in the banking sector and in microfinance. Mainstream lenders, assuming a positive correlation between poverty and credit risk, typically do not provide credit to those deemed poor. MFIs providing individual microloans generally hold the same view but distinguish between the less poor, who are deemed less risky, and the poorer, who are considered riskier. With the help of donors, technology, and know-how, MFIs can lend to the less poor, who are considered less risky in microfinance, although they are perceived as risky and thus non-bankable. Our analysis outlined in this chapter demonstrates the existence of poorer borrowers who are better credit risks than less poor borrowers. Most likely, these poorer borrowers have built or are planning to build a reputation as good payers. Such a reputation could be pledged to secure needed microloans.

Although MFIs might be aware of the existence of clients who are poorer than others but also more creditworthy, only the joint use of credit scoring and poverty scoring provides a complete picture. The literature on the joint use of credit scoring and poverty scoring is non-existent. In addition to shedding light on the non-linear relationship between poverty and credit risk, this

thesis proposes a novel approach to managing credit institutions with double or triple bottom-lines.

Chapter 8 Thesis summary and conclusions

Microfinance institutions serve areas where mainstream financial institutions cannot, offering financial services to microentrepreneurs and individuals with informal income. This provides a crucial avenue for financial inclusion. The lack of access to financial services, determined partly by poverty and information asymmetry, perpetuates a vicious cycle of poverty and informality. Without reliable proof of a steady income, mainstream financial institutions are reluctant to extend credit. They may even refuse to open payment accounts, thereby stalling the development of the working poor and their households.

MFIs circumvent information asymmetry by sending loan officers to visit borrowers' business premises and homes, engaging with their clients, suppliers, and neighbours, and requiring one or more co-signers with verifiable income streams. By building trustworthy relationships with first-time borrowers, MFIs can gradually offer them larger loans. However, initial transactions with new clients are costly, necessitating high interest rates and fees to break even. Unfortunately, these high costs can lead to adverse selection, where a disproportionately large share of risky borrowers applies for loans, and many manage to have their loan applications approved.

When loan officers and other decision-makers in MFIs equate relative wealth with creditworthiness or increased profitability, MFIs gradually drift away from their mission to empower poorer borrowers. If relatively wealthier loan applicants who receive financing also present higher risks, this mission drift could lead to increased credit losses, threatening the survival of the MFI. Raising loan prices to compensate for increased credit losses further exacerbates the adverse selection problem. In this context, credit scoring can help manage credit risk, enabling the MFI to remain sustainable. However, if credit risk and poverty are not strongly correlated, credit scoring alone will not help the MFI target poorer segments of borrowers. Nonetheless, it can provide the financial safety, allowing the MFI to focus on its mission while avoiding excessive credit risks.

If MFIs choose to lower the price of initial microloans to mitigate adverse selection and hope to recuperate lost profit once clients prove their creditworthiness and take larger loans, they may encounter a different form of adverse selection – one not typically seen in mainstream banking or discussed in financial literature. Relatively wealthier and riskier applicants may find

the lower prices attractive and increasingly seek MFI loans. If loan officers continue to equate wealth with creditworthiness, wealthier borrowers may crowd out poorer borrowers. While credit scoring can help avoid bad credit risks, it does not necessarily guide MFIs towards serving poorer applicants. Therefore, poverty scoring becomes essential for MFIs prioritising their social mission and sustainability.

Poverty scoring, as a cost-effective and accurate tool to assess the poverty level of loan applicants, signals donors and social investors that the MFI actively measures and adapts its outreach strategy to target poorer clients at both the institutional and individual client levels. The combined use of credit scoring and poverty scoring allows an MFI to identify ‘poor & safe’ loan applicants, if they exist. If most applicants are ‘vulnerable (in terms of poverty) and have average credit risk’, this dual approach enables the MFI to serve the less risky while strategically directing subsidies to extend outreach to poorer borrowers with slightly higher credit risk. By classifying applicants and borrowers into clusters based on poverty level and credit risk, an MFI can develop cluster-specific strategies that maximise social impact relative to profit.

This thesis undertakes a holistic examination of the need for and benefits of jointly using credit scoring and poverty scoring in microfinance institutions worldwide. It represents the first attempt to assess the theoretical and practical implications of combining these two scoring techniques.

This research encompasses an extensive literature review, significant theoretical developments, and quantitative analysis. Quantitative analysis was conducted using both MFI- and client-level data to validate the theoretical models and underlying hypotheses.

8.1 Summary of findings

The literature review allowed the construction of a consolidated conceptual framework of credit scoring. This framework can be applied to all types of loans issued to large groups of homogenous clients, including micro-borrowers. The conceptual framework of credit scoring was also used to describe poverty scoring and outline its differences. Overall, the conceptual framework helped in understanding what microfinance institutions expect from using credit scoring and poverty scoring separately and jointly.

From the review of microfinance-specific literature, we concluded that credit scoring adoption in microfinance follows a recurrent path, involving most of the mistakes made when adopting the technique in mainstream banking. Using strictly the developed conceptual framework of credit scoring when implementing the technique in an MFI would allow it to avoid biases and issues.

By analysing MFI-level data, we find that the use of credit scoring is associated with increased outreach in MFIs. MFIs that use credit scoring are larger and have more borrowers per loan officer. Since credit scoring does not create mission drift, we conclude that credit scoring contributes essentially to the mission of microfinance. We acknowledge that loan officers play a significant role in financing micro-borrowers. However, a lot of inefficiency and subjectivity is associated with their loan appraisal procedures. The informal environment in which microentrepreneurs operate determines a high information asymmetry between the MFI and the potential borrower. Inappropriate techniques for reducing this asymmetry result in huge opportunity costs for the borrower, potential borrower, lender, and society. Using credit scoring under certain conditions has significant potential for diminishing opportunity costs, increasing financial inclusion, and contributing to the development of regions where MFIs operate. Credit scoring is the accelerator pedal which can maintain a sustainable mix of growth and credit risk exposure. Thus, it can become a critical tool for expanding financial inclusion and developmental opportunities.

We have confirmed that the use of poverty measurement techniques, including poverty scoring, is associated with increased outreach to poor borrowers in MFIs. The policy implications for this conclusion centre on incentivising MFIs to adopt poverty measurement techniques. Encouraging the use of poverty scoring can help MFIs better target and serve poorer segments of the population, thereby enhancing financial inclusion. Poverty scoring can support poverty-related data collection and analysis, allowing new financial and non-financial products to be developed. Poverty scoring simplifies the monitoring and evaluation of the impact that microfinance, or related social programmes, had delivered through targeting poorer segments of the population. Since we have observed that loan officers inaccurately calculate the incomes of loan applicants, we conclude that any poverty measurement technique based on such calculations is inaccurate and probably misleading. Poverty scoring algorithms are not affected by such bias and are more reliable in estimating the poverty level of subjects.

Our attempt to find proof of the economic reasons why MFIs would implement poverty scoring has failed. This question was particularly relevant for profit-oriented MFIs, which might not be constrained by their owners or partners like non-profit MFIs are. We found that the use of a poverty measurement technique is neither associated with lower funding costs nor with lower operating costs. We found that the use of a poverty measurement technique is not associated with access to additional funding. We found that the use of a poverty measurement technique is associated with increased return on equity. It is probably associated with increased return on assets, but the statistical significance of this association is below the fixed threshold of $P \leq 0.1$.

The increased profitability of equity in MFIs that use a poverty measurement technique could be explained by the aggregate effect of different benefits that MFIs get from social investors, donors, and other stakeholders when MFIs signal the ability to measure the poverty level of their borrowers and thus show capacity to stay committed to the social mission of microfinance. The increased profitability of equity could also be explained by a more careful spending policy implemented by MFIs that want to signal their commitment to the social mission of microfinance.

Based on the low incidence of MFIs in our data samples that utilise both credit scoring and poverty scoring, we argue that the joint use of these techniques is not widespread in microfinance. MFIs that use both poverty scoring and credit scoring tend to have greater outreach to poor borrowers, as shown by the regression coefficients. Unfortunately, only the coefficient measuring the effect of poverty scoring (or any other poverty measurement technique) was found to be statistically significant. The coefficient measuring the impact of credit scoring, which had the same sign as the one measuring the impact of poverty scoring missed the $P \leq 0.1$ statistical significance mark. The fact that the use of credit scoring is not associated with a decrease in the social outreach of MFIs that also use poverty scoring is an encouraging finding. The lack of discord between the two scoring techniques, when used together, concerning MFIs' social mission, leaves room for synergies when these are possible.

In fact, if there is a non-linear relationship between poverty and credit risk in micro-borrowers, but if, when approaching extreme poverty levels credit risk increases significantly, at a certain level of outreach to poor borrowers, credit scoring might flag the loan applicants experiencing extreme poverty as very risky, slowing or stopping the downscaling effort of the MFI. We

found a positive moderate correlation between poverty and credit riskiness in the poorest third of clients of an MFI. We found a negative moderate correlation between poverty and credit riskiness in the wealthiest third of clients of the same MFI. We conclude that while poverty scoring can identify poorer segments of population, increasing outreach to poor borrowers, credit scoring might retard or stop such outreach effort if this is damaging the financial sustainability of the MFI.

The joint use of credit scoring and poverty scoring is neither associated with reduced financing costs nor with reduced operating costs in MFIs. The hypothesis that MFIs that use credit scoring and poverty scoring prefer to get additional financing at market rates instead of cheaper financing when they are already highly leveraged could not be proven either. In fact, the hypothesis that MFIs that use credit scoring and poverty scoring are highly leveraged also could not be proven.

Credit scoring is associated with lower profitability of MFIs, while poverty scoring and similar poverty measurement techniques are associated with higher profitability of MFIs. MFIs that use credit scoring and poverty scoring together register higher profitability due to the effect of poverty scoring and simultaneously lower profitability due to the effect of credit scoring. The joint effect is somewhere in between, potentially cancelling out both effects.

The use of credit scoring with poverty scoring is associated with increased social outreach of MFIs. This effect comes mainly from the use of poverty scoring. As we have shown, credit scoring, depending on how poverty and credit riskiness are associated, can support the social outreach of the MFI in tandem with poverty scoring or block it if poverty and credit riskiness are strongly associated and the outreach effort is endangering the financial sustainability of the MFI.

Using actual MFI data, we demonstrated the existence of ‘poor & safe’ borrowers – the ideal clients for MFIs from a double bottom-line perspective – which, unfortunately, were a minority. We identified, in line with theoretical estimations, a few ‘not poor & risky’ clients. Serving them would not advance either the social agenda of the MFI or its financial sustainability. We did not find ‘poor & risky’ borrowers, speculating that loan officers would have enough motives to reject loan applications which fall under such cluster, especially if they

are biased against poorer loan applicants. We found that loan officers mistakenly view wealth as a sign of creditworthiness.

The ‘poverty vulnerable & average credit risk’ borrowers were the largest cluster of borrowers in the sample of loans we analysed. This shows the challenge with which the analysed MFI is confronted, but probably most MFIs in developing countries. MFIs need credit scoring to rank loan applicants with average credit risk by credit score. Such a ranking would allow the MFI to have different underwriting approaches for those with relatively higher credit risk and those with relatively lower credit risk.

It could be reasonable from a financial perspective to reject all loan applicants from the ‘risky’ clusters, as well as some applicants from the ‘average’ risk clusters – those with the lowest credit scores. If among the rejected loan applicants are those who are from the ‘poor’ clusters, the MFI might decide to offer them specially designed small loans that give them access to finance while controlling credit risk and potential losses. MFI might decide to offer them group loans, supporting their ‘graduation’ to less risky clusters. Such transactions might not be profitable at the beginning or in the long run, and these would require some subsidisation. Eventual extra-profits made on ‘not poor & safe’ borrowers could be a source of internal subsidisation of poorer – more risky borrowers. Support from donors and social investors might be useful in advancing financial inclusion for poorer – more risky borrowers. The use of poverty scoring could be the flag that these organisations look for when deciding with which MFIs to work.

MFIs that decide to offer group loans to the poorest and riskiest loan applicants, supporting them with both financial and non-financial services to help them ‘graduate’ to a less risky and ideally less poor cluster, will need to use both credit scoring and poverty scoring. This will ensure that borrowers are correctly classified within the ‘poor & risky’ cluster. MFIs’ resources for addressing the economic empowerment of this cluster may be limited. To graduate, these borrowers need to demonstrate improved credit risk, which can be measured through credit scoring. Poverty scoring, however, is technically not required.

MFIs that offer only group lending will also need credit scoring if they aim to graduate certain borrowers to larger individual loans. However, such MFIs will need to acquire the credit

scoring algorithm first, as their own data may not include the individual credit behaviour of group borrowers. When borrowers form a loan group, the repayment behaviour of the group is recorded. Within groups with good repayment behaviour, struggling borrowers can be assisted by non-struggling borrowers. Conversely, within groups with poor repayment behaviour, struggling borrowers may be mixed with non-struggling ones, but the struggling borrowers will likely outweigh the good ones. Such MFIs will only need poverty scoring if they want to measure the progress out of poverty of clients, especially those who graduated.

If no financial institution in the country has provided individual credit to poorer loan applicants, it will be impossible to gather the data necessary to develop a credit scoring algorithm for borrower graduation. If poorer loan applicants have been systematically denied credit based on the assumption that they are too risky, the rules of credit scoring, when first implemented in an MFI, will require the algorithm to reject the profiles of loan applicants who were previously denied by loan officers. This is because their past behaviour is unknown, and this uncertainty could pose a threat to the MFI's sustainability if these borrowers are indeed risky.

The rules of credit scoring also require the MFI to gradually issue loans to profiles that were previously rejected by loan officers and, consequently, by the initial credit scoring algorithms. This requirement is necessary to generate repayment pattern data for new credit risk profiles – in this case, poorer borrowers. If MFIs overlook this requirement, which entails a certain temporary vulnerability to credit risk, poorer borrowers will not receive individual credit and will remain financially excluded. Their potential good loan repayment patterns will remain unknown.

This is not a weakness of credit scoring. Rather, it underscores that credit scoring is designed to estimate the credit risk of future loan transactions based on the repayment patterns of past transactions with similar profiles. It is the responsibility of the MFI to provide the repayment patterns of missing profiles from which new credit scoring algorithms can 'learn'. If this task is neglected, credit scoring algorithms designed to reject loans to unknown profiles will inadvertently perpetuate existing biases.

8.2 Contribution to theory

This thesis is the first attempt to methodically investigate the joint use of credit scoring and poverty scoring in microfinance. It sheds light on various aspects related to the use of credit scoring in microfinance, poverty scoring, and joint use.

A thorough literature review on credit scoring, taken in chronological order, resulted in a conceptual framework for credit scoring applicable across various loan markets, including microfinance. It helps both practitioners and academics understand credit scoring, especially its possibilities, benefits, and costs when applied in microfinance. The literature review identified attempts to use credit scoring in microfinance which were repeating the mistakes made when credit scoring was developing in mainstream finance. The author warns about such historical recurrences which are both unproductive and spread the miscontent in the technique to other institutions which might benefit from credit scoring.

Using regression analysis, the thesis finds that credit scoring aids in expanding financial inclusion without drifting from the mission of microfinance. This is particularly important for developing economies where financial inclusion is central to the development of the unemployed with entrepreneurial potential. Loan officers play a crucial role in microfinance, but their appraisal procedures can be inefficient and subjective. High information asymmetry in microfinance can result in significant opportunity costs. Accurate credit scoring can help reduce these costs and improve financial inclusion.

The thesis finds that the use of poverty scoring is associated with increased outreach to poorer borrowers. It goes without saying that robust poverty measurement supports better data collection, product development, and impact evaluation, enhancing overall financial inclusion. Poverty scoring seems to be the only technique that balances effectiveness with efficiency. Client-level data show that loan officers do not know or do not need to estimate the poverty level of the loan applicant as long as declared revenues seem credible and allow to structure a sound loan deal.

The expected economic benefits of poverty scoring for MFIs, such as reduced financing and operating costs, were not proven. However, poverty scoring is associated with higher return on

equity (RoE), while credit scoring often correlates with lower return on assets (RoA). The combined use of these techniques impacts profitability metrics differently.

The joint use of credit scoring and poverty scoring is not widespread. While credit scoring and poverty scoring can complement each other, their combined use does not significantly impact financing or operating costs. Further research is needed to explore potential synergies or conflicts of the two scoring techniques in high-poverty contexts.

Client-level analysis identified ‘poor & safe’ borrowers as ideal for MFIs from both social and financial perspectives, though they are rare. The largest group in the analysed MFI, but probably in most MFIs, is ‘vulnerable & average credit risk’ borrowers, highlighting the challenge for MFIs. Credit scoring helps in better ranking and decision-making, potentially allowing for tailored loan offerings and subsidisation for higher-risk borrowers. The observation that wealthier borrowers may be mistakenly viewed as more creditworthy emphasises the need for accurate credit scoring.

The thesis probably makes the most important contribution to the concepts of adverse selection and information asymmetry in microfinance as a field of finance.

8.3 Limitations

This research is not safe from confirmation bias. The author has probably looked predominantly at the facts that would confirm expected results. Although it tries to address both MFI-level and client-level data, not all aspects related to the use of credit scoring and poverty scoring, independently and jointly, have been addressed. Important aspects certainly have been overlooked.

Information asymmetry defines the microfinance space. Loan officers collect data from micro-borrowers who generally operate informal microbusinesses. In these conditions, loan applicants tend to overestimate revenues and underestimate, often without realising, expenses and underlying risks. Such inaccuracies contaminate client-level data but also can affect MFI-level information. Certainly, to a certain degree, these inaccuracies have affected the data and possibly the conclusions of this thesis. Our hope is that, in most cases, errors were distributed

randomly and did not seriously affect the averages and thus the regression coefficients, which constituted the basis for most quantitative conclusions.

8.4 Policy recommendations

This thesis demonstrates that the use of poverty scoring in microfinance institutions is associated with increased outreach to poorer micro-borrowers, which aligns with the social mission of microfinance. The benefits of poverty scoring, such as the ability to classify borrowers, at low cost, according to their probability of experiencing poverty, track their progress out of poverty, and assist in thematic data collection for various purposes – including monitoring and evaluation – have been outlined. Additionally, poverty scoring data can support the development of new financial and non-financial products for poorer populations. It has also been noted that poverty scoring can serve as a signal for donors and social investors. These could provide benefits leading to increased profitability.

The primary policy recommendation regarding poverty scoring is to encourage MFIs to adopt and utilise it. For stakeholders, including policymakers and regulatory authorities, the recommendation is to support and incentivise MFIs in implementing poverty scoring. Several non-profit initiatives, which provide reliable poverty scorecards free of charge for countries with a high concentration of poor populations, along with supporting documentation, can significantly ease the implementation process.

Implementation does incur costs: loan application forms – both paper-based and digital – need to be updated to incorporate the necessary fields. Loan officers will require training on how to collect the new data and ensure its accuracy. Departments such as analytics, monitoring, and reporting may also need guidance on how to effectively use and leverage the newly collected data.

Data collection for poverty scoring may increase the workload of loan officers. However, it can reduce their workload if, prior to implementing poverty scoring, they were required to estimate borrowers' poverty levels through direct income measurement or other less accurate and more time-consuming methods.

There are no significant drawbacks to implementing poverty scoring, aside from the costs of implementation and ongoing maintenance on the investment side, as well as the costs associated with new data collection on the operational side. If an MFI claims to serve a larger proportion of poor borrowers than it actually does, poverty scoring will expose this discrepancy, potentially leading to negative consequences for the institution. One potential risk associated with poverty scoring is that the revealed probability of a loan prospect experiencing poverty may lead the loan officer to stigmatise the applicant, which could result in the loan being refused or the loan amount being reduced. The use of credit scoring alongside poverty scoring can help mitigate this issue.

This thesis demonstrates that the use of credit scoring in microfinance institutions is associated with an increase in the number of micro-borrowers, which aligns with the social mission of microfinance. This growth, accompanied by credit risk control, also supports the economic mission of MFIs, which is to ensure long-term survival and profitability.

While free poverty scorecards are available for many countries, free credit scorecards for micro-borrowers are generally not accessible. Credit bureaus may sell a credit score alongside a credit report for a prospective micro-borrower however, these credit scores may have limited credit risk predictive power. This is primarily because many socio-demographic, business-demographic, financial indicators – spanning both the household and the micro-business – as well as loan product characteristics are typically unavailable in the data collected by credit bureaus. Although past credit behaviour data from lenders who report to credit bureaus is accessible, not all credit bureaus are permitted to store positive information. Some credit bureaus are legally restricted to collecting only data about delinquencies, and laws may also limit the retention period for negative information, allowing borrowers to clear their credit reports of bad data if such behaviour occurred several years ago.

Custom-made poverty scoring algorithms, which can integrate data from credit reports collected by the MFI, offer the advantage of relying on a wide range of variables from which a subset of strong, uncorrelated factors can be selected. As each MFI tends to attract a specific type of clientele, tailored credit scoring algorithms are more likely to capture these unique characteristics, thereby offering improved credit risk discrimination power. However, the development of custom credit scoring algorithms can be costly and often requires external

consultancy. This represents an investment that should be repaid over time through faster and more accurate credit decisions. Implementation and maintenance of these algorithms also require additional resources. MFIs that attempt to develop their own credit scoring systems may end up with biased or low predictive-power scorecards if the proper procedures for developing credit scoring algorithms are not adhered to. Poorly managed credit risk can lead to serious financial difficulties.

Public authorities interested in fostering the sustainable growth of the microfinance sector should encourage the use of credit scoring in MFIs. When the probabilities of default for individual loans are known, MFIs can implement precise credit loss provisioning. Credit scoring helps control credit risk and ensures that approval criteria are applied uniformly, free from bias or discrimination. Lenders of funds to MFIs should also promote the use of credit scoring to allow MFIs manage portfolio credit risk effectively. Good management can ensure a good pricing for such funds. The promotion of credit scoring should be accompanied by the dissemination of prudential guidelines to ensure the proper use of such tools. A poorly structured loan will default even if it is assigned a good credit score – when the debt burden is too heavy, repayment delinquencies are inevitable regardless of the credit score.

Credit scoring enables a centralised, uniform adjustment in the lender's credit risk appetite. If an MFI wishes to be more aggressive in the market, it can lower the rejection threshold (cut-off score). Conversely, if the MFI seeks to reduce its exposure to credit risk, it can raise the rejection threshold so that the riskiest loans which were previously approved are now either rejected outright or subjected to more rigorous underwriting.

A national poverty scorecard can be used across the country, provided there are no significant regional disparities. A credit scoring algorithm can be safely applied to the same population from which the loan repayment patterns used to develop the algorithm were derived. However, an MFI operating in urban areas may face challenges when using the same credit scoring algorithm in rural areas. While the algorithm may retain its credit risk discrimination power in rural areas due to similarities in repayment patterns observed among urban clients, it is prudent to test the algorithm's performance in new environments. One should note that testing is not easy since bad credit behaviour often manifests months or even years after loan disbursement. Only fraudulent loans tend to default within the first few months. Microfinance typically

involves short-term, frequent loans, which provides a conducive environment for the effective application of credit scoring.

The key policy recommendation of this research highlights the necessity of jointly using credit scoring and poverty scoring, as this is the only method capable of preventing two types of adverse selection in microfinance. The first type is the classical adverse selection, which occurs when risky loan applicants disproportionately increase as interest rates rise. The second type, specific to microfinance, is the adverse selection in which non-poor loan applicants disproportionately increase when interest rates fall. We have demonstrated that the correlation between poverty and credit risk can be either positive or negative in microfinance, depending on the depth of poverty. If loan officers mistakenly equate wealth with creditworthiness, which is not always accurate, serving primarily wealthier borrowers could lead to greater credit risk and undermine the social mission of microfinance.

An MFI that seeks to balance both financial survival and its social mission must be able to distinguish between ‘poor & safe’ borrowers, ‘poor & risky’ borrowers, and ‘not poor & safe’ borrowers. It should avoid the ‘not poor & risky’ group entirely and aim to limit the ‘poor & risky’ pool to a level it can safely manage. Such understanding would enable the development of internal subsidisation schemes to offer financial inclusion to ‘poor & risky’ borrowers, or to seek external support. The joint implementation and use of credit scoring and poverty scoring reduces information asymmetry on two key levels: credit risk and poverty levels. Accurate client-level information can be effectively communicated to stakeholders, thereby reducing information asymmetry at the MFI level. Generally, this transparency can be beneficial at multiple levels: client, MFI, and industry-wide.

These recommendations are applicable to markets that involve the provision of services with a credit component to populations who, despite being empowered by such services, are generally excluded due to poverty. While microfinance serves as the reference market, the findings and recommendations could extend to other similar contexts outlined in this research.

8.5 Suggestions for further research

By analysing a sample of first-time micro-borrowers financing their basic agricultural activities, we identified a small cluster of ‘poor & safe’ borrowers – the ideal segment for any

MFI. However, the question remains whether such cases are truly rare in that particular market and similar economies or if the MFI in question inadvertently excluded most poor loan applicants, including those who are safe, due to the absence of credit scoring.

National poverty surveys conducted in most developing countries provide statistics on household poverty levels, but no national or regional initiatives have been observed to measure the credit risk of poorer segments of the population. Understanding how poorer populations are distributed across credit risk levels would be invaluable not only for the microfinance industry but also for their clients. If ‘poor & safe’ borrowers are concentrated in significant numbers, MFIs could prioritise targeting these segments. Conversely, if such borrowers are scarce, it would prompt donors, social investors, and local public authorities to mobilise subsidies effectively and efficiently to promote financial inclusion.

Our analysis reveals that, overall, there is a moderate and inverse correlation between credit risk and poverty among the clients studied: poorer clients tend to be safer borrowers. This finding is compelling, as it suggests that poorer borrowers place significant value on building and maintaining their reputations, which they view as a critical asset for securing loans. However, this poverty-creditworthiness relationship breaks down and reverses among the poorest clients, who are riskier from a credit risk perspective. Borrowers who are not extremely poor can use their modest material possessions as a safety net when repayment issues arise, while those without valuable assets cannot. For each MFI, it would be crucial to understand how credit risk and poverty correlate and to determine the point at which this correlation becomes unsustainable for the institution.

We also imagined a possible three-dimensional tool when we developed the poverty-credit risk matrix, which we recommend MFIs use to guide their outreach strategies. In addition to poverty (first dimension) and credit risk (second dimension), this ‘decisional cuboid’ also incorporates the ecological impact of microloans (third dimension). Such an approach would require the development of some ‘ecological scoring’.

As climate change intensifies, green finance is becoming increasingly important, particularly in developing countries, which are especially vulnerable. Extreme weather events disrupt daily activities and damage crop cultivation, which is critical for both food security and export

economies in many regions. Additionally, rising sea levels pose significant challenges for coastal communities. Green finance aims to support investments in climate-resilient infrastructure and sustainable practices, helping these nations adapt to and mitigate environmental risks. It focuses on projects that balance economic growth with environmental protection, much like how microfinance seeks to balance economic growth with social outcomes and financial inclusion.

Currently, the largest DFIs provide green finance to local financial institutions in developing countries. These financial institutions on-lend received ‘thematic’ funds to eligible green investment projects. The eligibility of these projects must be validated by the lender before financing and often reassessed by the DFI after the green investment is made. This validation might require confirmation that the equipment or technology procured with green funds comes from a list of pre-approved vendors, or, in the case of more complex projects, a full assessment by specialised experts. However, such prior approvals are nearly impossible to implement in microfinance institutions due to their prohibitively high costs. A ‘green scoring’ system, developed on the principles of poverty scoring, could make green financing more feasible for microfinance institutions. Further research in this area could have significant implications for the future of green microfinance.

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