DISCRIMINATION BY MICROCREDIT OFFICERS: THEORY AND EVIDENCE ON DISABILITY IN UGANDA

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Abstract: This paper studies the relationship between a microfinance institution (MFI) and its credit officers when the latter discriminate against a group of the target population. Using survey data from Uganda, we provide evidence that credit officers are more biased against disabled borrowers than other employees. In line with the evidence, we then build an agency model of a non-profit MFI and a discriminating credit officer. Since incentive schemes are costly and the MFI’s budget is limited, even a non-discriminating welfare-maximizing MFI may prefer paying smaller incentivizing compensation, and letting its credit officer discriminate to some extent.

Keywords: Microfinance; Discrimination; Credit Officers; Incentives; Disability.
JEL codes: G21, O16, J33, L3.

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1. Introduction

Claiming that altruistic and benevolent organizations like microfinance institutions (MFIs) might discriminate against some of their customers may sound like an oxymoron. However, organizations are complex, and you cannot expect every single person working for an MFI to be totally impartial. Some individuals may be truly benevolent, and sincerely support their institution’s agenda. Others may contribute on the basis of their expected returns and be affected by the same biases as workers in other organizations. Some of them may therefore be prejudiced against parts of the population and behave according to their prejudices.

It is fair to recognize that staff in MFIs is often motivated by a genuine desire to be useful and to do good. Microfinance is advocated by international institutions and sponsored by business people and leading foundations. Their reputations would be put at risk if the institutions they support were suspected of discriminating against customers based on race, gender, or other characteristics. MFIs are therefore \textit{prima facie} unlikely to consciously discriminate against some sub-groups of their potential clientele.

However, evidence of discrimination on the loan market abounds. The evidence goes back at least to Black \textit{et al.} (1978), who provide survey-based evidence that race matters in mortgage loan allocation. Using information collected by the Federal Reserve Bank of Boston, Munnell \textit{et al.} (1991, 1996) spurred a large literature by finding that non-white applicants are significantly more likely to be denied a mortgage loan than white applicants with similar profiles. In his literature survey, Ross (2005) shows that this result survives a series of refinements.

More importantly for the microfinance industry, discrimination is also detected in small business lending. Cavalluzzo and Cavalluzzo (1998) find that businesses held by Hispanics and blacks face higher loan denial rates than those owned by whites. Blanchflower \textit{et al.} (2003) report that black-owned small businesses are about twice as likely to be denied credit as white-owned ones, holding all other factors constant. Cavalluzzo and Wolken (2005) and Blanchard \textit{et al.} (2008) confirm those results.

Admittedly, those pieces of evidence originate in the US, but there is ground to believe that discrimination in credit allocation also exists in developing countries, where populations are often ethnically heterogeneous and few legal barriers to discrimination exist. A direct piece of evidence from outside the US is provided by Storey (2004), who shows
that, in Trinidad and Tobago, loan applications from African small-business owners are more likely to be denied than others. In the same vein, Buvinic and Berger (1990), Fletschner (2009), and Agier and Szafarz (2010, 2011) provide evidence that women are more credit-rationed than men by MFIs. Lastly, Lewis (2004) concentrates on the issues facing businesswomen with disabilities in Zambia and Zimbabwe.

Moreover, studies, notably in India and Latin America, have exhibited discriminatory practices. In some cases, discrimination is direct: belonging to a given community generates social obligations and economic deprivation, as shown by Thorat (2002) with “caste discrimination”. In other cases, discrimination is indirect: lower human capital endowment is associated with lower access to education, causing a part of the population to be pushed to poorly-paid “dead-end jobs” (Knight, 1985). As stated by Patrinos (2000), indigenous, ethnic, racial, and linguistic minorities tend to be in an inferior economic and social position in comparison with the rest of the population.

Discrimination is thus a disappointing but acknowledged reality worldwide. Therefore, questioning its existence in microfinance not only makes sense, but also is particularly relevant as poverty and discrimination often overlap (Patrinos, 2000), and access to credit has proven instrumental to the poor. Microfinance portfolios are known to exhibit biases in favor of some customers, such as traders and urban customers. Whether those biases originate from efficiency motivation or from bigotry among MFI staff is still mostly unexplored. Unfair loan allocation may hamper the MFIs’ growth by hiding “artificial gaps” between supply and demand under efficiency claims. In that line of thought, de Janvry et al. (2006) show that efficiency-enhancing lending innovation hurts the weaker segments of the population and increase social differentiation.

In line with Dymski (2006) and many others, we define discriminatory lending as denying loans with a higher probability and/or granting loans with more stringent terms on the basis of observable characteristics unrelated to the MFI’s mission. Cramm and Finkenflügel (2008) and Mersland et al. (2009) point out that discrimination by MFI staff is a major reason why disabled people are hindered in access to microfinance. Indeed, although MFIs market fair lending policies, few disabled people access their services.

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1 This definition extends the definition proposed by Schreiner et al. (1996, p.849), “Discrimination is defined as providing smaller loans and/or providing loans with more stringent terms to borrowers who are identical with respect to creditworthiness but who differ with respect to characteristics unrelated to creditworthiness, such as race.” Indeed, in welfare-maximizing institutions, creditworthiness might not be the bottom line for loan attribution. Our definition is compatible with any kind of mission statement, whether social or commercial.
Among MFI staff, credit officers are a key channel through which discrimination may operate. Indeed, decentralization gives considerable leeway to credit officers who spend up to 75% of their working time outside of the office (McKim and Hughart, 2005), and are difficult to control. Incentives are, therefore, more appropriate than monitoring.\(^2\) Over the last decade, incentive pay has become increasingly common in MFIs.\(^3\) The share of MFIs that resort to staff incentive schemes grew from 6% in 1990 to 63% in 2003 (McKim and Hughart, 2005). Nevertheless, existing incentive schemes are associated rather to financial output than to social mission, which makes them mostly inefficient against discriminatory practices in welfare-maximizing institutions.\(^4\)

Surprisingly, little academic research in microfinance takes credit officers as their main focus, let alone as a source of discrimination. This paper aims at filling this gap. It presents empirical evidence from Uganda that credit officers tend to discriminate against disabled customers more than other staff. The evidence suggests that discrimination is due to a distaste for, as opposed to biased beliefs about, serving disabled customers. Based on this premise, a formal model then investigates how a welfare-maximizing MFI may use incentive contracts to deter its credit officers from discriminating against minority applicants. Since incentive contracts are costly and budget is limited, the MFI faces a trade-off between fighting discrimination and raising outreach. Welfare maximization may thus not imply complete eradication of discriminatory practices. In equilibrium the MFI may be better off paying a smaller incentive premium, and letting its credit officers discriminate to some extent.

The rest of the paper is organized as follows. Section 2 presents a survey from Uganda providing evidence that credit officers discriminate more than other employees. Section 3 sets up the formal model. Section 4 concludes.

\(^2\) Although most MFIs claim having credit committees, the actual decision is often left to the credit officer, either alone or in team with the branch manager. In cases where a supposedly more independent committee makes the decision, credit officers still have ample scope to express their prejudice, since decisions are taken based on the information they provide.

\(^3\) Most contributions on this issue come from practitioners (Développement International Desjardins, 2003; Holtmann and Grammling, 2005).

\(^4\) The costs of discrimination are not easy to assess, as they are opportunity costs for both the MFI and the unserved population. Most microfinance markets are supply-driven. Therefore, discrimination may appear cost-free to many MFIs, as it does not impede growth and fairly good returns. However, as competition is increasing (McIntosh and Wydick, 2005) discrimination may ultimately be costly for MFIs. Likewise, leaving aside ethical considerations, anti-discrimination measures in access to credit could be needed from an economic development perspective.
2. Discrimination by credit officers: Evidence

In microfinance methodologies such as solidarity groups, village banking, and individual lending, credit officers play a key role in screening loan applicants. They meet applicants face to face, and might, therefore, be inclined to discriminate against some of them. Although screening criteria are fairly standardized, credit officers are difficult to monitor. Due to decentralization and poor supervision, they can discretionarily grant loans to their preferred applicants rather than serve the whole target population of the MFI. Privileged borrowers could, for instance, belong to the officers’ social network. Additionally, credit officers may be reluctant to interact with some minority groups, such as the disabled. Although discrimination by microcredit officers is difficult to assess because of data availability restrictions, it is highly plausible. In this section, we argue that the disabled can be subject to discrimination, and we present evidence of such discrimination, based on a survey conducted in Uganda in 2008-2009.

2.1. The disabled face taste-discrimination

According to the United Nations (2008), approximately 10% of the global population has disabilities, and 80% of the disabled live in developing countries. Moreover, among those who live on less than one dollar a day, one in five has a disability. Although only a small fraction of the disabled is unable to work, 80 to 90% of them have no formal job. As a consequence, they turn to self-employment (UN, 2008). Few have access to microfinance. In Uganda, while the incidence of disability ranges from 3.5% (Population and Housing Census, 2002) to 20% (Uganda Demographic and Health Survey, 2006), depending on the statistical method, only 0.5% of MFIs’ customers are disabled (Mersland et al., 2009).

The low incidence of disabilities among MFIs’ customers cannot be explained by higher credit risk only. Indeed, Martinelli and Mersland (2010) observe that the disabled in Uganda run viable small businesses even without access to external credit. Therefore, we argue that their lower probability of getting a loan cannot only be attributable to lower creditworthiness.

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5 On the importance of credit officers, see also Fuentes (1996), Warning and Sadoulet (1998), and Schreiner (2000).
6 Studies have documented that women tend to be more credit-rationed than men by MFIs (Buvinic and Berger, 1990; Baydas et al., 1994; Agier and Szafarz, 2010)
More generally, researchers have repeatedly demonstrated that being disabled is associated with exclusion, similarly to race, sex, and tribal discrimination. As Neufeldt (1995) points out, disability is essentially a social construct with roots in societal attitudes. Accordingly, Johnson and Lambrino (1985) attribute more than one third of wage differences between the disabled and the non-disabled to taste-discrimination. Evidence suggests that even anti-discrimination bills do not eradicate discrimination against the disabled (see Barnes and Oliver, 1995 for the UK, and Beegle and Stock, 2003 for the US). In the rest of this section, we analyze survey data collected in Uganda in 2008-2009. The employees of eight MFIs were questioned on their attitudes and beliefs about disabled customers.

2.2. The survey

The data were collected by the Association of Microfinance Institutions of Uganda (AMFIU) in a joint initiative with the National Union of Disabled Persons of Uganda (NUDIPU), whose aim is to increase disabled people’s access to mainstream microfinance services. The Norwegian Association of the Disabled (NAD) supports AMFIU and NUDIPU in their efforts.7 The project includes training for 750 staff members in 75 MFI branches in issues related to microfinance and disability. In 24 branches, the start-up of training consisted in filling out the questionnaire of this survey. In addition to reporting personal data and their position in the branch, the respondents were asked to rate on a one-to-five scale their beliefs about microfinance and disability. The original aim of the survey was to identify areas for joint AMFIU/NUDIPU efforts. The survey does also serve the research purpose in this paper.

Eight MFIs are represented in the database, ranging from two small Savings and Credit Cooperatives (SACCOs) to the largest MFIs in Uganda. The 24 branches are located across the country in eight out of Uganda’s 80 districts. The dataset consisting in 231 respondents is representative for staff working in Ugandan MFIs.

2.3. Evidence of taste-discrimination among credit officers

The study focuses on the answers to two questions of the survey addressing discrimination. The respondents were asked to rate on a one-to-five scale their agreement with the two following statements:

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7 One of the authors has participated as a consultant for NAD in their efforts to increase outreach of microfinance to disabled people in Uganda.
1. “I believe that one of the reasons why we have few disabled customers is because we often unconsciously marginalize or discriminate them”.

2. “I believe that in this branch we never discriminate people because of their disability”.

Given that discrimination is a highly sensitive topic that can lead to the so-called “social desirability bias” (Nederhoff, 1985), the statements are formulated in a plural form (“we”) and not in a singular form (“I”) in order to be less offensive to the respondents. Nevertheless, we interpret the reactions to these statements as directly related to the respondent’s own behavior.

Figure 1 displays the rating distributions for both statements, splitting the sample across credit officers and other employees (secretaries, office clerks, and branch managers). In both instances, ratings span the whole scale, and differences appear between credit officers and other employees. In figure 1a, the mode of distribution concerning the statement “we discriminate” is 4 (“partly agree”) for credit officers, and 1 (“fully disagree”) for other employees. Nearly 56% of the credit officers partly or fully agree with the statement, while only 30% of the other employees do. In other words, while a majority of other employees consider that they do not discriminate, credit officers concede that they often do.

Fig. 1: Rating distributions for the statements on discrimination
Fig. 1a: Statement 1: “we often discriminate”  Fig. 1b: Statement 2: “we never discriminate”

Similar conclusions can be drawn from figure 1b, which displays the rating distribution for the statement “we never discriminate”. Again, significant differences appear between the two groups of respondents. Namely, the share of credit officers who agree with
the statement is lower than the share of other employees that do. Conversely, 63 percent of
credit officers fully disagree with the statement against 49 percent for other employees.

Overall, the raw figures suggest that discrimination is more prevalent among credit
officers than among other MFI employees. Likely because credit officers are in a position to
exert discrimination, they do it more than others. To check whether this result resists the
introduction of control variables, we now turn to econometric analysis.

For both statements, we regress the rating on the respondent’s characteristics. Since
the explained variables are discrete and ordered, we resort to ordered logit models.8 A dummy
explanatory variable captures whether the respondent is a credit officer. The sign of the
associated coefficient signals whether credit officers tend to discriminate more or less than
their co-workers against the disabled.

Discrimination, if any, may be due either to a genuine distaste for the disabled or to
the belief that the disabled are riskier customers. To disentangle these two explanations, we
use the rating (same scale) of a third statement:

3. “I believe that being disabled is associated with higher risk of loan default”.

If an employee believes, rightly or wrongly, that the disabled are riskier clients, then he/she
might discriminate against them without any distaste. This is the gist of the theory of
statistical discrimination, which originates in Phelps (1972) and Arrow (1973). Controlling for
the rating of statement 3 allows disentangling statistical from taste-based discrimination à la
Becker (1957).9 The dataset also allows controlling for the respondent’s characteristics. The
estimated models include explanatory dummies for having a disabled relative, being a female,
and having at least three-year work experience. Respondents with a disabled relative should
be not only less prejudiced, but also better informed about what the disabled can do. Their
reactions to statement 3 therefore provide some clue on the true capacity of the disabled to run
a business. We have no prior on the impact of gender, but the role of women in microfinance
has been emphasized (Armendariz and Morduch, 2010). Lastly, experience may affect the
beliefs on disabled borrowers.

8 Using ordered probit does not significantly affect the results. These results are available upon request.
9 Given the nature of our data, this argument needs to be understood in a relative way (credit officers versus
other employees).
Table 1: Ordered logit regression results with the explained variable being the reaction to the statement: “I believe that one of the reasons why we have few disabled customers is because we often unconsciously marginalize or discriminate them”

<table>
<thead>
<tr>
<th></th>
<th>(1.1)</th>
<th>(1.2)</th>
<th>(1.3)</th>
<th>(1.4)</th>
<th>(1.5)</th>
<th>(1.6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Credit officer</strong></td>
<td>0.696</td>
<td>0.691</td>
<td>0.666</td>
<td>0.646</td>
<td>0.713</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.30)**</td>
<td>(2.27)**</td>
<td>(2.03)**</td>
<td>(1.89)*</td>
<td>(1.87)*</td>
<td></td>
</tr>
<tr>
<td><strong>Higher default</strong></td>
<td>0.0441</td>
<td>0.0665</td>
<td>0.113</td>
<td>0.0864</td>
<td>0.0756</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
<td>(0.54)</td>
<td>(1.00)</td>
<td>(0.76)</td>
<td>(0.61)</td>
<td></td>
</tr>
<tr>
<td><strong>Disabled relative</strong></td>
<td>-0.587</td>
<td>-0.583</td>
<td>-0.597</td>
<td>-0.314</td>
<td>-0.278</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.05)**</td>
<td>(2.15)**</td>
<td>(-2.33)**</td>
<td>(1.14)</td>
<td>(0.93)</td>
<td></td>
</tr>
<tr>
<td><strong>Woman</strong></td>
<td>-0.314</td>
<td>-0.278</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.14)</td>
<td>(0.93)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Work experience</strong></td>
<td>0.0836</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.82)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Cluster-robust absolute z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The ordered logit models are estimated with cluster-robust standard errors to control for within-branch correlations. The results are provided in tables 1 and 2, respectively. The picture that emerges from both tables is consistent. In table 1, the baseline regression indicates that being a credit officer yields higher discrimination. The Wald Chi-squared statistic for the likelihood ratio test confirms that adding the credit officer dummy improves the fit. Regression (1.2) captures no relationship between believing that the disabled exhibit lower creditworthiness and acknowledging discrimination, which suggests that statistical discrimination is not at work here. Regression (1.3) shows that the impact of being a credit officer is robust to controlling for the respondent’s belief about credit risk, while this belief remains insignificant. Regression (1.4) to (1.6) include additional controls but leave the main result essentially unchanged.

Among the controls, only the dummy for having a disabled relative passes the ten-percent significance test with a negative coefficient. This finding lends credence to interpreting the dependent variable as a valid indicator of individual discriminatory behaviour. It is also reminiscent of Dymski’s (2006) statement that the lack of “cultural affinity” may hurt minority loan applicants.

Moreover, a bivariate logit regression (not reported here) in which the belief is explained by the credit officer dummy reveals no link between the two variables, meaning that the belief of credit officers is similar to that of other respondents.
Table 2 shows that credit officers disagree more than others with the statement “we never discriminate”. Table 2 also confirms that responses on discrimination are independent from beliefs about the disabled creditworthiness. Again, these findings are robust to the inclusion of additional controls. The only difference with table 1 is the absence of any significant impact of having a disabled relative.

Table 2: Ordered logit regression results with the explained variable being the reaction to the statement: “I believe that in this branch we never discriminate people because of their disability”

<table>
<thead>
<tr>
<th></th>
<th>(2.1)</th>
<th>(2.2)</th>
<th>(2.3)</th>
<th>(2.4)</th>
<th>(2.5)</th>
<th>(2.6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit officer</td>
<td>-0.612</td>
<td>-0.62</td>
<td>-0.615</td>
<td>-0.655</td>
<td>-0.744</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.37)**</td>
<td>(2.51)**</td>
<td>(2.24)**</td>
<td>(2.38)**</td>
<td>(2.77)***</td>
<td></td>
</tr>
<tr>
<td>Higher default</td>
<td>-0.125</td>
<td>-0.13</td>
<td>-0.136</td>
<td>-0.142</td>
<td>-0.125</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.87)</td>
<td>(0.94)</td>
<td>(0.91)</td>
<td>(0.99)</td>
<td>(0.77)</td>
<td></td>
</tr>
<tr>
<td>Disabled relative</td>
<td>0.0895</td>
<td>0.183</td>
<td>-0.000409</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.5)</td>
<td>(0.00097)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Woman</td>
<td></td>
<td></td>
<td></td>
<td>-0.303</td>
<td>-0.316</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.97)</td>
<td>(0.82)</td>
<td></td>
</tr>
<tr>
<td>Years of experience</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.14</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.1)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>187</td>
<td>210</td>
<td>186</td>
<td>182</td>
<td>179</td>
<td>165</td>
</tr>
<tr>
<td>Log pseudolikelihood</td>
<td>-260.60</td>
<td>-293.98</td>
<td>-257.47</td>
<td>-251.90</td>
<td>-245.34</td>
<td>-218.60</td>
</tr>
<tr>
<td>Wald Chi²</td>
<td>5.63</td>
<td>0.76</td>
<td>7.41</td>
<td>8.04</td>
<td>21.14</td>
<td>25.15</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.00833</td>
<td>0.00395</td>
<td>0.0128</td>
<td>0.013</td>
<td>0.016</td>
<td>0.0199</td>
</tr>
</tbody>
</table>

Cluster-robust absolute z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In a probit model, the coefficients cannot be directly interpreted as marginal effects, because the model is non-linear. Marginal effects can, however, be inferred from regressions for each combination of independent variables. Consider for instance a male employee, with no disabled relative, little experience, and no clear-cut opinion on the disabled creditworthiness. From table 1 (statement: “we discriminate”) and specification (1.6), such an employee has probability 0.39 of picking rating 4 (“partly agree”) if he is a credit officer, and 0.32 otherwise. From table 2 (statement: “we never discriminate”) and specification (2.6), the same employee has probability 0.25 of picking rating 1 (“strongly disagree”) if he was a credit officer, and 0.14 otherwise.

Overall, our findings underline a strong correlation between acknowledging discrimination and being a credit officer. A straightforward interpretation of this correlation is that the credit officers are the MFI employees who are indeed in a position to discriminate.

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11 i.e., picking rating 3 for statement 3.
and therefore do. Moreover, our results show that discrimination is not attributable to biased beliefs. Hence, we conclude that credit officers tend to exert taste-based discrimination. In the next section, we investigate the consequences of such a bias for socially-oriented MFIs.

3. A model of discrimination by a biased credit officer

The previous section has made the case for the existence of taste-discrimination by microcredit officers. Obviously, such discrimination is at odds with the MFI’s poverty-alleviation mission, and thus leads to a typical agency problem. This section theoretically examines how a socially-oriented MFI can address this issue and design optimal wage incentives to combat taste-discrimination from its credit officers.

3.1. The model

Let us consider a socially-oriented MFI facing a credit officer’s taste-discrimination against an identifiable group of loan applicants. The MFI has defined its target population (i.e., the pool of applicants), and delegates clientele selection to a credit officer. All members of the target population are unbanked. They are either poor ($\kappa = P$) or less poor ($\kappa = L$), and either favored ($i = F$) or discriminated against ($i = D$) by the credit officer. The previous section suggests that the disabled provide a meaningful example of $D$ group. Due to the decentralization of the microfinance lending methodology, only credit officers are able to trustfully assess poverty levels. Indeed, assessing poverty levels requires detailed information, notably on income and cash flows, and credit officers are the only MFI’s agents who gather such information. Consequently, a biased credit officer can easily cheat on an applicant’s poverty level and strategically hide private pieces of information. On the other hand, the characteristics that drive discrimination are generally easily observable (gender, disability, race, etc.). Therefore, we assume that the MFI observes the $F/D$ characteristic.

In this setting, any candidate has a bidimensional vector of characteristics:

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12 See Méon and Szafarz (2011) on discrimination as an agency problem.
13 One could argue that MFIs should not hire prejudiced agents in the first place. While this is the obvious first-best solution, it is not always implementable on the field as finding good credit officers (in terms of clientele screening) may reveal arduous and costly, and prejudice may take time to be detected. Moreover, some prejudices (linked to caste, for instance) may be so widely spread that truly unbiased credit officers are rare. Therefore, second-best solutions often need to be investigated.
14 Contrary to Aubert et al. (2009), we do not include the client’s ability as a relevant characteristic, as the MFI’s objective function is purely social and sustainability is not discussed. Moreover, in our setting, only the loan allocation process is considered, not the associated credit risk.
\((i, \kappa), i \in \{D, F\}, \kappa \in \{P, L\}\)  

The pool of applicants features the following proportions of the four categories: \(\gamma_{DD}, \gamma_{FP}, \gamma_{DL}, \gamma_{FL}\), with \(\gamma_{ik} > 0 (i = D, F; \kappa = P, L)\) and \(\sum_{i=D,F} \sum_{\kappa=P,L} \gamma_{ik} = 1\). The credit officer offers loans on the basis of the applicants’ characteristics \((\kappa, i)\). All loans are identical and normalized to 1. A loan allows the borrower to seize a riskless investment opportunity that yields return \(r\) (identical for all borrowers).

Following its mission statement, the MFI is benevolent and group-blind. Its objective is to maximize welfare, measured by the expected social utility of its clients:

\[
\text{Max} \sum_{j=1}^{n} E[U_j],
\]

where \(n\) is the number of clients, to be determined endogenously, and \(E[U_j]\) is the expected utility of client \(j\). We assume decreasing marginal utility of income. Consequently, any given return results in a larger extra utility for a poor than for a less poor borrower. The extra utility brought by a loan is \(\Delta u_p\) to a poor and \(\Delta u_L\) to a less poor, with \(\Delta u_p > \Delta u_L\). The MFI, therefore, prefers granting loans to the poor.

The MFI also faces a budget constraint. Its fixed budget \(B\) is to be allocated to both loans and the credit officer’s wage \(\omega\)

\[
B = \omega + n.c,
\]

where \(n\) is the number of loans to be fixed by the MFI, and \(c\) is the positive constant marginal cost associated to a loan,\(^{15}\) in addition to the credit officer’s wage. The fixed budget assumption is consistent with the fact that most socially-oriented MFIs are mostly subsidized NGOs that fail to attract profit-oriented investors (Hermes and Lensink, 2007; Cull et al., 2009). Typically, microfinance is a labor-intensive industry. Indeed, labor costs amount to 50 to 70\% of total administrative costs supported by MFIs (Holtmann and Grammling, 2005).

\(^{15}\) Cost \(c\) is the sum of the operational and monitoring costs associated to a loan and the expected default loss, minus the present value of the interest differential (the loan rate minus the financing rate). For the sake of simplicity, we do not split \(c\) into its components and do not differentiate between types of clients, as the costs and benefits unrelated to the credit officer’s wage are not our main focus.
Unlike the MFI, the credit officer is biased against the $D$ group. This assumption is consistent with the previous section’s main finding and with the evidence reported by Cavalluzzo and Cavalluzzo (1998) that minorities-owned small businesses face higher denial rate attributable to taste-based discrimination. Due to time constraints, the credit officer only meets a limited number of applicants every period, and allocates one loan in each period. For simplicity, we assume that each choice is to be made between two applicants\textsuperscript{16} randomly drawn from the pool. The biased credit officer would never spontaneously grant a loan to a member of the $D$ group unless both applicants belong to that group.

Being aware of the credit officer’s bias but unable to observe poverty levels, the MFI chooses a second-best strategy, and pays an incentive wage that inversely relates to the credit officer’s discriminatory intensity. The credit officer’s reaction to that incentive is modeled in probabilistic terms. When facing two applicants with respective characteristics $(D, P)$ and $(F, L)$, the officer offers the loan to the $(D, P)$ candidate with probability $\lambda \in [0, 1]$. Variable $\lambda$ measures the officer’s propensity not to let prejudice interfere with loan attribution.

Prejudice makes the credit officer’s expected utility decrease with $\lambda$. The credit officer has the following expected utility:

$$E[V] = E[\omega] - \frac{1}{2} d \lambda^2 \quad (d \geq 0)$$

where $\omega$ is the credit officer’s wage. Parameter $d$ captures the intensity of the credit officer’s bias against the $D$ group. As $d$ increases, the officer’s expected disutility of choosing a very poor $D$ applicant over of a less poor $F$ applicant increases. Parameter $d$ gauges the officer’s aversion to the $D$ group relative to his/her utility of consumption. An unbiased officer is characterized by $d = 0$, but there is no upper limit on that parameter.

The distribution of outcomes of the loan attribution is summarized in table 3. The characteristics of the two applicants are displayed in the first row and the first column of table 3, respectively. Each cell of table 3 gives the characteristics of the applicant, and, whenever relevant, the associated probabilities.

\textsuperscript{16} Although we have set this number to two for the sake of simplicity, the argument can easily be generalized to larger numbers.
**Table 3: Outcomes of loan granting**

<table>
<thead>
<tr>
<th>Applicant 1</th>
<th>Applicant 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>(D, P)</td>
<td>(D, P)</td>
</tr>
<tr>
<td>(D, L)</td>
<td>(D, L)</td>
</tr>
<tr>
<td>(F, P)</td>
<td>(F, P)</td>
</tr>
<tr>
<td>(F, L)</td>
<td>(D, P) with prob. $\lambda$</td>
</tr>
</tbody>
</table>

When both applicants share the same poverty level, the credit officer systematically chooses an $F$ applicant, if any. The decision becomes trickier when the poorest applicant belongs to the $D$ group. The officer’s bias could indeed be high enough for him/her to allocate the loan to a less poor $F$ applicant rather than a very poor $D$ applicant. In such a situation, the credit officer’s prejudice can be detrimental to the MFI’s mission and result in mission drift.17

17 The term « mission drift » usually designates the situation where the financial sustainability constraint makes the MFI move away from its poverty-alleviation mission (see Gosh and Van Tassel, 2008; Armendariz and Szafarz, 2011). In our model, the mission drift would rather be due to discrimination by the credit officer.
Therefore, an incentive is needed to make the credit officer choose applicant \((D,P)\) over applicant \((F,L)\).

In our model, the applicant’s poverty level is unobservable to the MFI, and thus cannot serve as an instrument for incentivization. Instead, we assume that the incentive is inversely related to the credit officer’s bias. The rationale for introducing anti-discrimination incentives is twofold. Firstly, most socially-oriented MFIs would consider fighting discrimination as a subsidiary mission. For instance, many MFIs focus on women even in male-dominated societies (Morduch, 1999). Secondly, group membership is observable to the MFI, and discriminated-against groups are typically poorer than the rest of the population. Therefore, anti-discrimination incentives may be viewed as a second-best instrument.\(^{18}\) Specifically, we consider a standard linear contract with fixed component \(C\) and premium \(s\):

\[
\omega = C + s\lambda, \quad s \geq 0, \quad C > 0, \quad (5)
\]

The wage contract in (5) nests the standard contract in which the officer’s wage is a constant and \(s\) is set to zero.

From (3) and (5), the MFI’s budget constraint is:

\[
B = C + s\lambda + nc \quad (6)
\]

Eq. (6) shows that the MFI faces a trade-off. Increasing \(s\) augments the credit officer’s propensity to serve poor clients, but at the same time raises his/her wage, and so reduces the number of allocated loans, \(n\). The MFI has thus to trade off between serving the poor and allocating more loans.

To close the model, we specify the timing of the game (see Figure 1). The MFI first chooses \(n\) and \(s\) under the participation constraint, which states that the officer’s expected utility must exceed that provided by his/her outside option. The credit officer then determines \(\lambda\), and subsequently allocates the \(n\) loans. Lastly, the resulting MFI’s total utility is realized.

\(^{18}\) For instance, one may argue that disabled customers should be preferred by the MFI to make them equal in income generating capacity.
3.2. Equilibrium discrimination

The model is solved through backward induction. First, we describe the last player’s, i.e. the credit officer’s, reaction function. Then, we derive the contract offered by the MFI, which determines the outcome of the game.

The credit officer chooses probability $\lambda$, which represents his/her propensity not to let prejudice interfere with the hiring decision. Plugging the wage-scheme (4) into the officer’s objective function (3) yields:

$$\begin{align*}
\max_{\lambda \in [0,1]} \left\{ C + s\lambda - \frac{1}{2} d \lambda^2 \right\}.
\end{align*}$$

(7)

The first-order condition for that problem is:

$$\lambda = \frac{s}{d}. \tag{8}$$

Note that $\lambda$ increases with the MFI’s incentive instrument, $s$. Being a probability, $\lambda$ must take values between 0 and 1.\(^{19}\) This restriction may in turn lead to corner solutions for some parameter configurations. Therefore, one has:

$$\lambda^* = \begin{cases} 
\frac{s}{d} & \text{if } s \leq d \\
1 & \text{if } s > d 
\end{cases} \tag{9}$$

\(^{19}\) This might lead to the false impression that discrimination fully disappears when $\lambda$ is equal to one. Actually, the MFI is blind to discrimination taking place within poverty classes. Indeed, when facing two equally-poor applicants, the credit officer systematically chooses the $F$ applicant, if any. Pushing the argument to the extreme, if the pool were made of poor applicant only, then no $D$ applicant opposed to an $F$ applicant would ever get a loan.
The MFI designs the performance-based contract by anticipating its effects on the officer’s behavior. From table 4, the MFI’s utility of allocating a loan to applicant $j$ is the random variable defined by:

$$U_j = \begin{cases} \Delta u_L & \text{with probability } \Omega(\lambda) = \gamma_{DL}^2 + \gamma_{FL}^2 + 2\gamma_{DL}\gamma_{FL} + 2(1-\lambda)\gamma_{FL}\gamma_{DP} \\ \Delta u_P & \text{with probability } 1 - \Omega(\lambda) \end{cases}$$  \hspace{1cm} (10)$$

where probability $\Omega(\lambda)$ is a linear function of $\lambda$:

$$\Omega(\lambda) = (\gamma_{DL}^2 + \gamma_{FL}^2 + 2\gamma_{DL}\gamma_{FL} + 2\gamma_{FL}\gamma_{DP}) - 2\lambda\gamma_{FL}\gamma_{DP}$$

with:

$$\begin{cases} a = \gamma_{DL}^2 + \gamma_{FL}^2 + 2\gamma_{DL}\gamma_{FL} + 2\gamma_{FL}\gamma_{DP} \\ b = 2\gamma_{FL}\gamma_{DP} \end{cases}$$

As a consequence, the MFI’s problem states:

$$\text{Max } \sum_{j=1}^{n} E[U_j] = n \left[ a\Delta u_L + (1-a)\Delta u_P - b(\Delta u_L - \Delta u_P)\lambda \right]$$

\hspace{1cm} (11)

s.t.: $B = C + s\lambda + nc$

Let $Q = B - C$ be the MFI’s net budget, $A = a\Delta u_L + (1-a)\Delta u_P$ be the part of MFI’s expected utility that is independent from the officer’s behavior, and $\delta = \Delta u_P - \Delta u_L$ be the extra utility of granting a loan to a poor instead of a less poor. The MFI’s problem becomes:

$$\text{Max } E[U(s)] = \left( \frac{Q - s\lambda}{c} \right) (A + b\delta\lambda)$$

\hspace{1cm} (12)

Given the credit officer’s optimal reaction function in eq. (9), the optimal value for $s$ is either the interior point, $\bar{s}$, or the corner value, $d$. To compute $\bar{s}$, we rewrite the MFI’s objective function for $\lambda = \frac{s}{d}$:
\[ \sum_{j=1}^{n} E[U_j] = \frac{1}{cd^2} \left( -b \delta d s^3 - A s^2 + Qb \delta s + dQA \right) \] (13)

which leads to the following first-order condition:

\[ -3bd \delta s^2 - 2As + Q b \delta = 0. \] (14)

Since \( \Delta = A^2 + 3Qb^2 \delta d > 0 \), this second-degree equation has two real roots, but only one is non-negative (because \( \Delta > A^2 \)), and hence admissible given that \( s \) is a premium:

\[ \bar{s} = \frac{A + \sqrt{\Delta}}{3bd \delta} \] (15)

The MFI’s objective function reaches its global maximum for \( s^* = \bar{s} \) provided that \( \bar{s} \leq d \). Alternatively, if \( \bar{s} > d \), then (9) implies that the credit officer adopts the non-discriminatory behavior, namely \( \lambda^* = 1 \), so that the MFI has no incentive to offer a premium larger than \( d \). In this case, the MFI’s optimal premium is \( s^* = d \). In short, we have:

\[ s^* = \min\{d, \bar{s}\} \] (16)

The corresponding optimal value for \( \lambda \) is given by:

\[ \lambda^* = \begin{cases} \frac{\bar{s}}{d} & \text{if } s^* = \bar{s} \\ 1 & \text{if } s^* = d \end{cases} \] (17)

Expression (19) displays our key result. The equilibrium probability that the credit officer does not discriminate can be lower than one. Despite being a pure welfare-maximizer, blind to group membership, the MFI may thus tolerate some discrimination in equilibrium. The rationale for this result is that fighting discrimination is costly, not only in financial terms (higher wage), but also, and more to the point, in terms of outreach (less granted loans). Indeed, each extra dollar devoted to incentives reduces the number of loans. The MFI must
then trade off two evils: discrimination and poverty. If the officer’s taste for discrimination is high enough, then the social cost, in terms of foregone loans, of eradicating discriminatory behavior would be too large. In such a case, the MFI tolerates some discrimination because the marginal benefit of devoting a dollar to combating discrimination would be lower than the benefit of granting an extra loan.

Consequently, observing an MFI’s loan attribution biased against a minority group does not necessarily imply that this MFI is intrinsically biased against this group. It can alternatively be the case that the MFI delegates loan allocation to biased credit officers and cannot afford eradicating discrimination. From a managerial policy perspective, this result suggests that additional solutions must be found to combat discrimination, because wage incentives may reveal insufficient. Moreover, our result is obtained on the premise that the MFI maximizes social welfare. Therefore, a benevolent social planner would adopt the exact same behavior.20

4. Concluding remarks

So far microfinance practices have been studied in terms of efficiency and market segments. These factors largely explain why some poor are served by MFIs while others remain unserved. However, other reasons might be at work, like discrimination. This paper presents evidence that credit officers taste-discriminate against disabled people, and discusses how a socially-oriented MFI may mitigate discrimination by offering high-powered incentives. Using a formal agency model, we argue that well-designed incentive schemes might be part of the solution. However, because incentives are costly and budgets are limited, MFIs may sometimes better fulfill their mission by not fully eradicating discrimination. In a nutshell, a non-discriminatory MFI may tolerate some discrimination because eradicating it would be too costly in terms of outreach.

Before drawing policy recommendations from these results, several comments are in order. Firstly, designing adequate incentives is delicate. Initially, incentive schemes used by MFIs were based on a single criterion, typically the growth of loan portfolio. Over time, it appeared that growth targets were often met at the expense of credit quality. Consequently,

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20 In our setting, the MFI is hurt by discrimination only insofar as it interferes negatively with its social mission. Fighting discrimination is not the MFI’s final goal. A more drastic version of our model could include fairness to the MFI’s mission statement. If this were the case, the trade-off would still not automatically disappear. However, the incentive would be higher, and the non-discriminatory equilibrium would become more likely.
today’s MFIs increasingly combine criteria. Even so, the adjustment of credit officers to whatever set of incentives generates new biases.\textsuperscript{21}

Secondly, governance issues are more complex in socially-oriented organizations than in profit-oriented firms (Labie, 2001; Hartarska, 2005; Mersland and Strøm, 2009). In particular, discrimination is harder to tackle in welfare-maximizing institutions, where the profit-seeking mindset to build adequate incentives is lacking, a point raised by Aubert \textit{et al.} (2009). Stakeholders are indeed less likely to tolerate discrimination from socially-oriented institutions than shareholders and customers from profit-oriented firms. The recent crisis in the Indian state of Andhra Pradesh where pressure from credit officers has resulted in clients committing suicide has shown how detrimental microcredit officers’ malpractice can be for the whole microfinance industry. All in all, incentives are no quick fix to discrimination.

Additionally, anti-discrimination measures might paradoxically make the MFI deviate from its mission. It has been argued, for instance by Coate and Loury (1993), that such measures may in fact hurt the very population that they aim to help, by reinforcing stereotypes.

To circumvent the drawbacks of anti-discrimination incentive schemes, MFIs could adopt a hiring policy directed to credit officers biased in favor of discriminated-against groups, as illustrated by Biggs \textit{et al.} (2002), who put forward the role of ethnic networks, and d’Espallier \textit{et al.} (2009) who show that female CEOs increase the odds of serving female borrowers. Identifying credit officers with a bias in favor of disabled customers may, however, prove difficult. An alternative route could be to organize sensitivity training for credit officers. Indeed, our finding that the probability to discriminate decreases when one has a disabled relative suggests that tastes for discrimination are not static.

In conclusion, discrimination by MFIs deserves more attention than it has received so far. This contribution is intended to pave the way for further on-field investigations of discriminatory practices and designing adapted anti-discrimination tools aligned with the MFIs’ social mission.

\textsuperscript{21} As an example, Pamecas, a major network of credit unions in Senegal, set up a scheme mixing two indicators: quality of portfolio (measured by arrears) and growth (measured by debt outstanding). By not including the number of loans, Pamecas created an incentive for credit officers to focus on borrowers requiring sound but larger loans, therefore favoring a mission drift and ultimately leading Pamecas to reconsider its policy.
References


Appendix

Table A1: Characteristics of survey respondents (percentages)

<table>
<thead>
<tr>
<th>Credit officer</th>
<th>Disabled relative</th>
<th>Women</th>
<th>Years of experience &gt;2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>66.17</td>
<td>27.11</td>
<td>47.32</td>
<td>37.5</td>
</tr>
</tbody>
</table>

Table A2: Distribution of ratings (percentages)

<table>
<thead>
<tr>
<th>Rating</th>
<th>“I believe that one of the reasons why we have few disabled customers is because we often unconsciously marginalise or discriminate them”</th>
<th>“I believe that in this branch we never discriminate people because of their disability”</th>
<th>“I believe that being disabled is associated with higher risk of loan default”</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>22.81</td>
<td>22.67</td>
<td>30.84</td>
</tr>
<tr>
<td>2</td>
<td>15.35</td>
<td>6.67</td>
<td>24.67</td>
</tr>
<tr>
<td>3</td>
<td>9.21</td>
<td>8.44</td>
<td>14.98</td>
</tr>
<tr>
<td>4</td>
<td>29.82</td>
<td>15.11</td>
<td>11.89</td>
</tr>
<tr>
<td>5</td>
<td>17.11</td>
<td>45.78</td>
<td>11.89</td>
</tr>
<tr>
<td>n.a.</td>
<td>5.70</td>
<td>1.33</td>
<td>5.73</td>
</tr>
</tbody>
</table>
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