Microfinance and Gender: Is There a Glass Ceiling in Loan Size?

Isabelle Agier*
Ariane Szafarz†

This version: June 9, 2011

Abstract

Microfinance institutions serve a majority of female borrowers. But do men and women benefit from the same credit conditions ? We investigate this issue by presenting an original model and testing its predictions on an exceptional database including 34,000 loan applications from a Brazilian microfinance institution. The model determines the optimal loan size fixed by a gender-biased lender, depending on the borrower's creditworthiness and the intensity of the lender's bias. The empirical analysis detects no gender bias in loan denial, but uncovers disparate treatment with regard to credit conditions. In particular, we find a glass-ceiling effect. The gender gap in loan size increases disproportionately with respect to the borrower's project scale. The results are insensitive to the loan officer's gender.

Keywords: Microcredit, Microfinance, Gender, Discrimination, Women entrepreneurs.
JEL codes: O16, D82, G21, L31, J16.

*UMR 201 - Dveloppement et Socits (Paris I Sorbonne / IRD) and CERMi, Email: isabelleagier@gmail.com

†Universit Libre de Bruxelles (ULB), SBS-EM, Centre Emile Bernheim, and CERMi, Email: aszafarz@ulb.ac.be

"It is one of the injustices of the way that society is organized in Bangladesh that extremely able women, even those from better-off households, are unable to realize their entrepreneurial potential because their gender acts as a barrier to gaining access to the necessary resources. Men, even poor men, have always had more choices in terms of accessing economic opportunities than women from an equivalent class" Kabeer (2001, p. 83)

1 Introduction

Microfinance institutions (MFIs) offer tiny loans to poor entrepreneurs, among which a majority of women who typically benefit from smaller loans than men (Armendáriz and Morduch, 2010). According to Daley-Harris (2009), more than 70% of MFIs' clients were women in 2007.[1] For this reason, conventional wisdom tends to view microfinance as a tool for affirmative action. We challenge this view by building an analytical framework and delivering empirical evidence.

Previous papers have detected discrimination in small-business credit, but predominantly in the US.[2] Outside the US, the evidence is scarce, likely because of data unavailability. Notable exceptions include Storey (2004) who shows that, in Trinidad and Tobago, loan applications from Afro-descendant small-business owners are more likely to be denied than others. Besides, a study on Italian microfirms and self-employed individuals by Alesina et al.

[1] This rate reaches more than 80% for the poorest clients. Besides, Ferreira et al. (2010) highlight Brazil's disappointing performances in poverty reduction.

[2] Actually, the US lending industry is subject to specific regulations. The US anti-discrimination legal framework includes the Fair housing Act of 1968, the Equal Credit Opportunity Act (ECOA) of 1974 and the Home Mortgage Disclosure Act (HMDA) of 1975. In 1989, the Congress amended the former HMDA and made it mandatory for lenders to report the race and ethnicity of their loan applicants. Wide disparities in loan denial rates were subsequently exhibited by the Boston Federal Reserve Bank using the HMDA database. Based on denial rates, Munnell et al. (1996); Ross and Yinger (1999) and Han (2004) show that ethnic minorities (African-Americans and Hispanic-Americans) are facing larger loan rejection rates than white applicants with similar creditworthiness. In mortgage lending, evidence shows that black applicants face the worst denial rate (Schafer and Ladd, 1982; Ross, 2000) while female applicants are subject to disparate treatment (Ladd, 1998). Refining the existing econometric methodology, Blanchard et al. (2008) also find evidence of credit discrimination against black-owned and Hispanic-owned businesses, but not against white women. However, these authors do not separate black and Hispanic women from men, which makes it difficult to globally assess discrimination against female applicants. See also Cavalluzzo and Cavalluzzo (1998); Blanchflower et al. (2003); Cavalluzzo and Wolken (2005).

(2008) emphasizes that women pay higher interest rates although they exhibit a slightly better credit history. Bellucci et al. (2010) provide additional evidence on gender discrimination in Italian small-business lending.

Interestingly, Buvinic and Berger (1990) and Fletschner (2009) show that women keep being more credit-rationed than men by MFIs, while Mayoux (2002) mentions the "danger of "ghetto-ising" women within small loan programs." However, this evidence alone does not prove that the loan allocation process is biased. Indeed, women in developing countries are knowingly poorer than men,[3] and their entrepreneurial projects, logically, have smaller scopes. Hence, higher credit rationing could simply reflect lower expected creditworthiness. To circumvent this argument and check for disparate treatment attributable to pure taste-based discrimination (Becker, 1971), this paper compares denial rates and loan sizes for male and female applicants *with similar expected creditworthiness*.

Our first contribution is theoretical. Somewhat surprisingly, little is known about credit rationing associated to fixed-interest lending. Indeed, following the seminal paper by Stiglitz and Weiss (1981), the abundant literature on credit rationing concentrates on lending with risk-adjusted interest rates, which is common practice in the banking industry. On the opposite, MFIs offer fixed-interest loans, and tailor loan size to the applicant's expected creditworthiness (Morduch, 1999). This *modus operandi* is motivated by the need to stick to low operational costs in order to serve a large pool of poor borrowers. Moreover, the social performances of MFIs are often evaluated on the basis of average loan size (Armendáriz and Szafarz, 2011).

Our model combines two different - but not mutually exclusive - representations of gender bias: a fixed-cost-like bias (identical for all female applicants) that suggests pure prejudice, and a variable-cost-like bias (increasing with loan size) that captures the idea of stereotyping. In this framework, we discuss the consequences of gender-biased credit allocation with respect to the borrower's creditworthiness and to the nature and intensity of the lender's bias.

Our second contribution is empirical. We exploit data provided by a Brazilian MFI encompassing over 34,000 loan applications. The results show no sign of disparate treatment in loan approval. However, we uncover a significant gender gap in loan size, which disproportionately increases with respect to the borrower's project scale. Hence, our claim is that there is a glass-ceiling in loan size. Additionally, these findings are insensitive to the loan officer's gender. In conclusion, the good news is that access to credit is fair, while the

[3] According to ILO (2009), 75% of poverty worldwide is female.

bad news is that women face harsher loan downsizing than men, especially the ones with the largest business projects.

The paper is organized as follows. Section 2 presents the theoretical model. Section 3 describes the database. Section 4 investigates the impacts of gender on loan approval and loan size, taking into account a large spectrum of control variables. The glass ceiling in loan size is documented in section 5. Section 6 concludes.

2 The Model

The pool of loan applicants is denoted by P. Each applicant, $(x, g) \in P$, is characterized by two variables assumed independent: creditworthiness, $x \in X$, and gender, $g \in \{F, M\}$. Actually, the microfinance industry often claims that women are more creditworthy than men. Therefore, our model may be viewed as providing lower bounds for the impact of biased loan-allocation, rather than absolute values.

The risk-neutral MFI delegates screening and loan allocation to an officer who is assumed to be unbiased toward male applicants ($g = M$), but biased against female applicants ($g = F$). We also assume that the information is symmetric at least at the loan officer's level.[4]

The model has one period. All loans bear the same interest rate, r.[5] At time 0, the officer receives a loan request from applicant (x, g), and subsequently allocates a loan of size $LS = LS(x, g)$ (equal to zero, in case of denial) by maximizing the expected profit, $E\left[W\left(LS, x, g\right)\right]$, which equals the expected future repayment minus the costs. The costs combine the MFI's cost of capital, $r_0\,(r_0 < r)$, and the officer's psychological costs associated to serving women. The latter is split in two components. Firstly, the variable-cost-like component, $\delta_1 \in [0, 1]$, captures the idea of stereotyping regarding the entrepreneurial capabilities of women. As put forward by Buttner and Rosen

[4] At the MFI level (not considered in the model), information asymmetry is more likely because MFIs are highly decentralized. Hence, discriminatory practices can remain unnoticed by the MFI's stakeholders who do not observe the applicants' characteristics, which leads to a classical principal-agent problem. Highlighting this problem in a more general context, Méon and Szafarz (2011) show that taste-discrimination in hiring may result from such a principal-agent issue.

[5] This is common practice in microcredit institutions. Alternatively, the lending rate could be adjusted to the client's risk characteristics in x, but beside making the model more complex, this would not much affect the results. Also for the sake of simplicity, we ignore the operational costs.

(1988, p. 249) for US banks, *"the hypothesis that characteristics attributed to successful entrepreneurs were more commonly ascribed to men than to women. On the dimensions of leadership, autonomy, risk taking, readiness for change, endurance, lack of emotionalism and low need for support, bank loan officers rated women as significantly less like successful entrepreneurs compared to men."* Secondly, the fixed-cost-like component, $\delta_2 \geq 0$, represents pure prejudice, i.e. disliking lending to women.

The lender's maximization problem at time 0 thus reads:

$$\underset{LS \geqslant 0}{Max}\, E[W(LS, x, g)] = E[R(LS, x)] - LS(1 + r_0 + \delta_1 1_F) - \delta_2 1_F 1_{LS} \quad (1)$$

where $R(LS, x)$ is the stochastic gender-insensitive repayment from borrower (x, g) for a loan of size LS, $E[.]$ represents the expectation operator, 1_F is the gender dummy (equal to 1 when $g = F$), and 1_{LS} is the loan dummy (equal to 1 when $LS \neq 0$).

At time 1, the borrower reimburses the loan up to his/her current business revenue. We assume the existence of a penalty sufficiently high to deter strategic default. The borrower's revenue, denoted by y, is unknown at time 0. For the sake of simplicity, we assume that only two values are possible for y, depending on the state of the nature: a low value, $\underline{y}$, and a high value, $\overline{y}$. Each borrower (x, g) is characterized by his/her probability, $\pi(x)$, to generate the low revenue in the following way:[6]

$$y(x, g) = y(x) = \begin{cases} \underline{y} \text{ with probability } \pi(x) \\ \overline{y} \text{ with probability } 1 - \pi(x) \end{cases} \quad (2)$$

In order to eliminate the trivial cases where discrimination is sufficient to *ex ante* exclude all female applicants (irrespective of their profitability), we assume that: $\delta_1 \leqslant r - r_0$ and $\delta_2 \leqslant \frac{\overline{y}(r - r_0 - \delta_1)}{1+r}$. Indeed, gender biases that would violate either of these conditions can be easily detected by observing the absence of female borrowers, since the clientele's gender repartition is public knowledge.

At time 1, $y(x)$ realizes and borrower (x, g) repays $R(LS, x)$ where:

$$R(LS, x) = \min\{y(x), LS(1 + r)\} \quad (3)$$

Table 1 summarizes the six possible repayment situations, depending on the loan size (LS) and the borrower's realized revenue ($\underline{y}$ or $\overline{y}$). Repayment is deterministic for small loans ($LS \leq \frac{\underline{y}}{1+r}$), and otherwise stochastic.

[6]Parametrizing the borrowers in this way renders the expected repayment continuous with respect to creditworthiness. In practice, loans are reimbursed by installments, which materializes the possibility for partial loan reimbursement.

Table 1: Repayment $R(LS, x)$ depending on loan size (LS) and revenue (y)

Revenue y \ **Loan size** LS	$LS \leq \frac{y}{1+r}$	$\frac{y}{1+r} < LS < \frac{\bar{y}}{1+r}$	$LS \geq \frac{\bar{y}}{1+r}$
$\underline{y}$ [prob : $\pi(x)$]	$LS(1+r)$	$\underline{y}$	$\underline{y}$
$\bar{y}$ [prob : $1-\pi(x)$]	$LS(1+r)$	$LS(1+r)$	$\bar{y}$

Two notable observations can be drawn from table 1. First, loans larger than $\frac{\bar{y}}{1+r}$ are excluded since revenues are capped at $\bar{y}$. Second, as the objective function is continuous and piecewise linear with respect to LS, only three optimal loan sizes are feasible: $LS^* = 0$ (no loan), $LS^* = \underline{LS} = \frac{\underline{y}}{1+r}$ (small loan), and $LS^* = \overline{LS} = \frac{\bar{y}}{1+r}$ (large loan). Consequently, the expected profit simplifies to:

$$E\left[W(LS, x, g)\right] = \begin{cases} 0 & \text{if} \quad LS = 0 \\ \underline{LS}[r - r_0 - \delta_1 1_F] - \delta_2 1_F & \text{if} \quad LS = \underline{LS} \\ \pi(x)(1+r)[\underline{LS} - \overline{LS}] & \\ +\overline{LS}[r - r_0 - \delta_1 1_F] - \delta_2 1_F & \text{if} \quad LS = \overline{LS} \end{cases} \tag{4}$$

From the expected profits in eq.4, we determine the optimal loan size for male and female applicants in each parameter configuration. For male applicants we have:

$$LS^\star(x, M) = \begin{cases} \underline{LS} & \text{if} \quad \pi_0 \leq \pi(x) \\ \overline{LS} & \text{if} \quad \pi(x) < \pi_0 \end{cases} \tag{5}$$

where: $\pi_0 = \frac{r - r_0}{1+r}$. For female applicants, the result depends on the gender biases of the loan officer:

$$LS^\star(x, F) = \begin{cases} 0 & \text{if} \quad \pi_0 \leq \pi(x) \text{ and } r - r_0 < \delta_1 + \frac{\delta_2}{\underline{LS}} \\ \underline{LS} & \text{if} \quad \pi_0 \leq \pi(x) \text{ and } \delta_1 + \frac{\delta_2}{\underline{LS}} \leq r - r_0 \\ & \quad \text{or } \pi_0 - \frac{\delta_1}{1+r} \leq \pi(x) < \pi_0 \\ \overline{LS} & \text{if} \quad \pi(x) < \pi_0 - \frac{\delta_1}{1+r} \end{cases} \tag{6}$$

Eq.5 and eq.6 allow determining the gender gap in loan size, $\triangle^\star(x) = LS^\star(x, M) - L^\star(x, F)$, as displayed in Table 2. Interestingly, this table shows that not all female applicants are penalized to the same extent. The actual harm depends not only on the credit officer's biases, δ_1 and δ_2, but also on the applicant's creditworthiness, x.

Three scenarios are possible:

Table 2: Gender gap in loan size ($\triangle^\star$)

Gender biases: (δ_1, δ_2)	**Applicant's creditworthiness**		
	Low $\pi_0 \leq \pi(x)$	High $\pi_0 - \frac{\delta_1}{1+r} \leq \pi(x) < \pi_0$	Very High $\pi(x) < \pi_0 - \frac{\delta_1}{1+r}$
$\delta_1 + \frac{\delta_2}{\underline{LS}} > r - r_0$	Discriminatory denial	Downsizing	No gender gap
$\delta_1 + \frac{\delta_2}{\underline{LS}} \leq r - r_0$	No gender gap, $\triangle^\star = 0$	$\triangle^\star = \overline{LS} - \underline{LS}$	$\triangle^\star = 0$

1) In the *best-case scenario*, the loan officer is either unbiased ($\delta_1 = \delta_2 = 0$), or subject to a fixed-cost-like bias solely, and this bias is small ($\delta_1 = 0$ and $\delta_2 \leq \underline{LS}(r - r_0)$). In this case, male and female applicants get identical loans. The optimal loan size is $\overline{LS}$ if the borrower's probability of low revenue lies below threshold π_0 (high creditworthiness), and $\underline{LS}$ otherwise (low creditworthiness).

2) In the *average-case scenario*, the loan officer is subject to a variable-cost-like bias, and the combination with the potential fixed-cost-like bias is small enough ($\delta_1 > 0$ and $\delta_1 + \frac{\delta_2}{\underline{LS}} \leq r - r_0$) to avoid discriminatory loan denial. In this case, women with low-creditworthiness face no gender gap in loan size, while women with high-creditworthiness do. There is still a potential segment of women with very high creditworthiness $\left(\pi(x) < \pi_0 - \frac{\delta_1}{1+r}\right)$ who remain untouched by loan downsizing. However, this segment vanishes if both the loan officer is subject to a variable-cost-like bias solely, and this bias is large ($\delta_2 = 0$ and $\delta_1 \simeq r - r_0$).

3) The *worst-case scenario* $\left(\delta_1 + \frac{\delta_2}{\underline{LS}} > r - r_0\right)$ combines the features of the average-case scenario for high-creditworthiness women and loan denial for low-creditworthiness ones.

Most importantly for practical purposes, these three scenarios can be empirically disentangled provided that an adequate measure of creditworthiness is available. Firstly, case 3 implies disparate treatment in loan denial rates, while both cases 1 and 2 do not. Secondly, case 2 implies disparate treatment in loan size, while case 1 does not. Section 4 proposes an empirical analysis based on these two identification conditions. Before that, section 3 presents our database.

3 Data

Our database comes from VivaCred, a non-profit Brazilian MFI, and covers the eleven-year period 1997-2007. VivaCred offers credit to micro-entrepreneurs in Rio de Janeiro's low-income communities and neighborhoods. It focuses on urban (formal and informal) micro-businesses such as storekeepers, craftspersons, and service providers. VivaCred's activity started in 1996 in Rocinha, the largest *favela* in Rio. Later, branches opened in Rio das Pedras (1998), Copacabana - now in Gloria - (1999), Mar (2000), Santa Cruz (2002), and the city of Maca in Rio state (2004). Until 2009, VivaCred was mostly funded by the Brazilian Development Bank (BNDES). At the time, VivaCred integrated the national program *CrediAmigo* funded by *Banco do Nordeste*, a Brazilian public bank.

VivaCred's loans are accessible to micro-entrepreneurs with at least six months of business activity behind them. VivaCred asks no collateral, but discloses the identities of its defaulting borrowers in the national register (SPC), which is consultable by any institution supplying credit, including shops. This penalty for default is heavy. Indeed, beyond forbidding further access to credit, being registered in SPC brings serious troubles getting a cell phone contract or buying household appliances.

Like most MFIs, VivaCred has a fixed-interest lending policy based on credit rationing.[7] The loans bear a fixed 3.9% monthly interest rate[8] plus a one-shot registration fee (from 3 to 5%) that depends on the credit duration and the client's repayment history.

VivaCred's loan granting process is the following. For each application, a loan officer is designated to collect all relevant information on the applicant's and guarantor's situations,[9] and on the business characteristics and financial statements.[10] Subsequently, this loan officer makes a recommendation to the

[7] This way of doing raises ethical issues, as discussed by Hudon (2009).

[8] Over the period 1997-2007, the central bank monthly interest rate (celic) fluctuated from 0.89% to 2.58% (from 11.18% to 35.76% on a yearly basis). The monthly interest rates used by *Banco da Mulher*, a non-profit institution comparable to VivaCred were comprised between 3% and 5%. Meanwhile, *Fininvest*, a for-profit institution, was offering consumption loans with monthly rates reaching 12%.

[9] Namely: private and professional addresses, birth date, birth state, marital status, gender, dependent(s), profession, bank references, partner's ID, current account, family consumption, family external income, full credit history (as a borrower, a borrower's partner, or a guarantor). The database does not, however, include racial information. Actually, because of miscegenation, racial segmentation is difficult in Brazil (Sheriff, 2000).

[10] Namely: location, type of activity, age, bank references, formality, detailed assets and liabilities, expenditure and revenues, and number of employees.

credit committee,[11] which in turn makes the final decisions (loan acceptance or denial, and loan size).

Our dataset contains the characteristics of all - ultimately approved or denied - applications gathered by VivaCred's administration, as well as the loan officer's gender. Over the period, about 41,000 loans were solicited by 15,400 applicants. About 32,000 loans were granted to 11,400 borrowers. We cleaned the database by removing canceled applications, contracts with incomplete specifications, loans to VivaCred's employees, and the few group loans. As a result, we run this empirical study on 34,000 loan applications, among which 32,000 resulted in actual loans. Table 3 summarizes the global and gender-disaggregated descriptive statistics and tests for equal means between male and female applicants.

VivaCred claims no particular gender focus. Its clientele is balanced with 49.6% of loans granted to women entrepreneurs. Table 3 indicates that, on average, female applicants are two year older than male ones (45 versus 43), less likely married (43% versus 52%), and less often with dependents (51% versus 53%). Logically, external income (i.e., business-unrelated income earned by any household member) is gender-neutral (around BRL 210 per month). Moreover, the guarantor's and borrower's genders are unrelated.

Male and female applicants differ not only in personal situations, but also in business characteristics. Indeed, table 3 shows that female-owned businesses are typically smaller, in terms of both profit and staff size, and less often formal.[12] The equal mean t-tests confirm that women apply for smaller loans than men (BRL 1,254 versus BRL 1,526). Besides, while 34% of male applications are motivated by investment (as opposed to liquidity), this proportion falls to 29% for female applications.

Men and women face similar approval rates (about 95%), which is consistent with the absence of any fixed-cost-like gender bias as discussed in section 2. On the other hand, women receive smaller loans, both in absolute terms (BRL 846 versus BRL 1074) and proportionately to the requested amount (73.7% versus 74.7%). According to our model, this can result from the presence of variable-cost-like gender bias. However, an analysis taking creditworthiness factors into account is necessary before jumping to conclusions.

[11] The term "credit committee", used by VivaCred, is somewhat misleading since it refers to a single person. Depending on the requested amount, the "credit committee" is either the branch manager or a senior loan officer.

[12] Fajnzylber et al. (2011) show that Brazilian micro-firms that go formal experience higher levels of revenue and profits.

Table 3: Global and gender-disaggregated descriptive statistics

	Global Mean	Std. Dev.	Mean M. App.	Mean F. App.	t-test[c]
Female applicant[b]	0.496	0.50			
Loan approval[b]	0.945	0.228	0.944	0.946	−0.00213
Requested amount (X 100 BRL)[a]	13.92	12.42	15.26	12.54	2.722***
Loan size (X 100 BRL[a])	9.61	9.98	10.74	8.46	2.282***
Applicant profile					
Age (in years)	42.20	11.97	41.24	43.17	−1.925***
Married[b]	0.47	0.50	0.52	0.43	0.0962***
At least one dependent[b]	0.52	0.50	0.53	0.51	0.0169**
External income (X 100 BRL)[a]	2.13	3.76	2.11	2.16	−0.04
# former loans in VivaCred	2.25	3.27	2.35	2.15	0.202***
# former loans with delay (> 30 days)	0.038	0.205	0.043	0.035	0.0077***
# previous experiences as guarantor in VivaCred	0.74	2.11	0.89	0.6	0.282***
Business characteristics					
Business profits (X 100 BRL)[a]	9.19	13.44	10.26	8.09	2.177***
Sector (trade = 1, other = 0)	0.53	0.50	0.49	0.56	−0.0760***
Formal business[b]	0.06	0.23	0.07	0.05	0.0165***
Staff size	0.63	2.20	0.72	0.54	0.175***
Credit characteristics					
Investment purpose[b]	0.32	0.47	0.34	0.29	0.0518***
Loan repayment purpose[b]	0.09	0.29	0.08	0.1	−0.0171***
Guarantor's involvement[b]	0.92	0.27	0.93	0.92	0.00756**
Observations		33,851			

[a]Monetary variables are given in the Brazilian currency corrected for the Rio de Janeiro state inflation index - IPC. The Brazilian Real (BRL) fluctuated between 0.26 USD and 0.96 USD over the period 1997-2007.

[b]Dummy variable: Yes = 1, No = 0

[c]t-test for equal means between genders; *** p<0.01, ** p<0.05, * p<0.1

4 Gender-specific Loan Approval and Loan Size

Differences in denial rates are the cornerstone of the empirical literature on discrimination in the lending industry. Tests have been used for detecting discrimination based on race, gender, or ethnicity.[13] Applied to gender, the classical testing methodology involves probit regressions including an explanatory gender dummy and suitable proxies for creditworthiness. Gender discrimination is then suspected if the gender dummy has a positive impact on the probability of loan denial.

[13]See Lacour-Little (1999) for a survey on models and methods on discrimination in mortgage lending, and Blanchard et al. (2008) for a survey on discrimination in small-business lending.

In our sample, however, the lender's decisions go beyond loan denial/approval, involving loan size determination too. Fortunately, the requested amount is observable for all applicants (whether selected or rejected), allowing to test for gender-sensitivity in project scopes. This represents a methodological novelty for the literature on discrimination in lending.

On the flip side, the requested amount depends on the applicant's characteristics (see table 3). Thus, including the requested amount among the regressors may bring multicollinearity. To address this issue, we depart from the classical estimation approach, and opt for partial least square (PLS) regressions (Wold et al., 1984; Tenenhaus, 1998; Helland, 1990).

Following the predictions of the model presented in section 3, a gender bias in loan allocation may create excess credit rationing for women entrepreneurs in two different ways: excess loan denial on the one hand, and excess loan downsizing on the other. Therefore, our empirical investigation involves both a probit model for loan approval, and a linear model for loan size.

The control variables are the ones typically used to assess creditworthiness. They include the borrower's personal information (age, marital status, external income, presence of dependents, guarantor's involvement, and guarantor's gender if involved), the business characteristics (profitability, sector, business status, staff size, and loan purpose), as well as the borrower's credit history in VivaCred (number of former loans as a client and as a guarantor, previous delays). Year dummies account for external economic factors. We also include dummy variables for the branch and for the loan officer's gender.

Loan approval is represented by the dummy variable defined by: $A_i = 1$ if applicant i gets a loan; $A_i = 0$ otherwise. The corresponding probit model is:

$$P(A_i = 1) = \Phi(b_F\, F_i + b_R\, RA_i + \mathbf{b}'_{\mathbf{X}}\, \mathbf{X_i}) \tag{7}$$

where $\Phi(.)$ is the Gaussian distribution function, F_i is the gender dummy ($F_i = 1$ if applicant i is a woman; $F_i = 0$ otherwise), RA_i is the requested amount for applicant i, and $\mathbf{X_i}$[14] is the vector summarizing the J control variables for applicant i. The associated coefficients are b_F, b_R, and vector $\mathbf{b_X}$, respectively.

A linear specification with the same independent variables is used for loan size:

$$LS_i = c_F F_i + c_R\, RA_i + \mathbf{c}'_{\mathbf{X}}\, \mathbf{X_i} + \epsilon_i \tag{8}$$

[14] Bold characters represent vectors.

where LS_i is the loan size obtained by applicant i. Denied applications are captured as zero loans. The coefficients associated to the explanatory variables are denoted by c_F, c_R, and vector $\mathbf{c_X}$, respectively.

As a pre-treatment against multicollinearity for both eq.7 and eq.8, we clean variable RA from its dependencies on the other explanatory variables through PLS estimation. More precisely, in the first step we determine the residual requested amount, RRA, namely the requested amount cleaned from the impacts of gender and controls:

$$RA_i = a_F F_i + \mathbf{a'_X X_i} + RRA_i \tag{9}$$

In the second step, we explain the approval probability and the loan size by the gender dummy, the controls and the residual requested amount. The approval probability (eq.7) then becomes:[15]

$$P(A_i = 1) = \Phi[(b_F + b_R a_F)F_i + (\mathbf{b'_X} + b_R \mathbf{a'_X})\mathbf{X_i} + b_R\, RRA_i] \tag{10}$$

Similarly, the loan size regression (eq.8) then becomes:

$$LS_i = (c_F + c_R a_F)F_i + (\mathbf{c'_X} + c_R \mathbf{a'_X})\mathbf{X_i} + c_R\, RRA_i + \epsilon_i \tag{11}$$

By combining the coefficients estimated, respectively, from eq.9-10 and eq.9-11, we isolate the "pure" effects of the requested amount on, respectively, loan approval and loan size.

Table 4 presents the marginal effects at the mean for the probit regressions (specifications (1)-(3)) and the estimated coefficients for the loan size regressions (specifications (4)-(6)). The results in (1) and (4) are obtained from uncorrected requested amounts (OLS estimation), while the results in (2), (3), (5), and (6) are cleaned for multicollinearity, and are therefore based on residual requested amounts (PLS estimation). Moreover, in (3) and (6), the loan officer's gender is taken into account through both a dummy and an interaction term with the applicant's gender.

In all specifications, the approval probability appears to be gender-insensitive, which is consistent with the picture that emerges from the descriptive statistics (table 3). In contrast, the impact of the applicant's gender on loan size is significantly negative in all specifications, meaning that, all other things equal (including the requested amount), women undoubtedly get smaller loans than men.

[15] Actually, applying PLS to probit regressions may slightly distort the marginal effects, but the significance thresholds remain adequate, which is our main concern.

Table 4: Loan approval and loan size regressions

	Loan approval			Loan size		
	Probit marginal effects at mean			Linear regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
Female applicant	0.000275	0.00144	0.00408	-31.20***	-93.69***	-89.92***
	(0.00198)	(0.00199)	(0.00287)	(5.931)	(6.480)	(8.884)
Requested Amount (RA)	-1.12e-05***			0.595***		
	(8.71e-07)			(0.00277)		
Residual RA (RRA)		-9.70e-06***	-9.37e-06***		0.573***	0.574***
		(9.27e-07)	(9.26e-07)		(0.00315)	(0.00315)
Female officer			-0.00835***			-39.39***
			(0.00282)			(9.280)
Female applicant			-0.00500			-7.609
& Female officer			(0.00411)			(12.69)
Observations	33851	33851	33851	33851	33851	33851
R-squared				0.716	0.661	0.661

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Monetary variables in deflated BRL. Column (1) refers to eq.7 (without cleaning for multicollinearity), columns (2) and (3) refer to eq.10, column (4) refers to eq.8 (without cleaning for multicollinearity), and columns (5) and (6) refer to eq.11. **Controls:** # Former loans, # experiences as guarantor, # past delays, Marital status, dependent(s), age, guarantor involvement, investment purpose, repayment purpose, external income, business profits, sector, formal business, staff size, year dummies, and branch dummies.

Importantly, the comparison of the gender effects in (4) and (5) clarifies the origin of the gender gap in loan size. In specification (4), the gender dummy coefficient is equal to (-31.20), while in (5) the global gender effect - which melts together the direct and indirect (through the requested amount) effects - reaches (-93.69). Thus, women do indeed get smaller loans, but principally because, under similar circumstances, they ask for smaller loans than men. Still, in a discrimination-free environment, loan officers could have learned that, for a given level of creditworthiness, women tend to introduce less inflated requests. Consequently, unbiased officers should adopt a less stringent credit-rationing policy toward female applicants. In reality, we observe the opposite. Women ask for less money than men with the same characteristics, and get even less.

In the context of small-business lending, disparate treatment likely originates from long-lasting stereotypes against women entrepreneurs as observed, for instance, by Buttner and Rosen (1988). Notwithstanding their social mission, MFIs delegate credit allocation to loan officers who are not necessarily immune to gender stereotypes. As social psychologists claim (Fein and Spencer, 1997; Kunda and Sinclair, 1999), stereotyping and prejudice are common features in human behavior.

Regarding the officer's gender (specifications (3) and (6)), we find significantly negative coefficients in both the approval and loan size regressions,

but no significant gender interaction between the applicant and the officer. Thus, female officers are more reluctant to grant loans and supply smaller loans, irrespectively to the applicant's gender.

To sum up, the credit approval rate is not affected by the applicant's gender, but loan size determination is detrimental to female borrowers. As a consequence, the estimations exclude both the best-case scenario (no disparate treatment at all) and the worst-case scenario (disparate treatment in the approval rate and the loan size) described in Section 2. However, because linearity was assumed from the start, the specifications used in this section fall short of assessing how the gender gap in loan size varies according to the project scale. Better suited specifications accounting for the possibility of a glass-ceiling effect are proposed in the next section.

5 Is there a Glass Ceiling in Loan Size ?

We already know that, globally, women get smaller loans than men with similar characteristics. This section examines whether all women are treated alike, or whether some of them face harsher treatment. In particular, a glass ceiling effect in loan size would be observed if women with higher expected revenue would be more rationed.

In order to assess the dependency of the loan size to the interaction of the project scope and the borrower's gender, we successively consider two specifications: one with gender-specific slopes, and the other with gender-specific quadratic terms.

The first specification includes gender-specific slopes :

$$LS_i = c_F F_i + c_R\, RRA_i + c_{RF}\, RRA_i F_i + \mathbf{c}'_{\mathbf{X}}\, \mathbf{X_i} + \epsilon_i \tag{12}$$

where LS_i is the loan size, F_i is the gender dummy ($F_i = 1$ if applicant i is a woman, $F_i = 0$ otherwise), RRA_i is the residual requested amount, and vector $\mathbf{X_i}$ summarizes the controls. A significantly negative value for c_{RF} would capture the glass-ceiling effect.

The second specification includes gender-specific quadratic terms:

$$LS_i = c_F F_i + c_R\, RRA_i + c_Q\, (RRA_i)^2 + c_{QF}\, F_i (RRA_i)^2 + \mathbf{c}'_{\mathbf{X}}\, \mathbf{X_i} + \epsilon_i \tag{13}$$

In this equation, a significantly negative value for c_{QF} would capture a glass-ceiling effect stronger than in eq.12 since the specification is quadratic.

Table 5: Estimations of the glass ceiling effect

	Loan size	
	(1)	(2)
Female applicant (F)	-94.10***	-60.31***
	(6.435)	(6.611)
RRA	0.625***	0.537***
	(0.00394)	(0.00370)
RRA*F	-0.143***	
	(0.00653)	
RRA^2		2.01e-05***
		(7.61e-07)
RRA^2*F		-3.03e-05***
		(1.78e-06)
Observations	33851	33851
R-squared	0.665	0.668

Standard errors in parentheses; *** p<0.01
Monetary variables in deflated BRL.
Same controls as in table 4, col (4) and (5).

The two specifications featured in table 5 present similar explanatory powers. Both confirm the presence of a glass ceiling effect.[16] Indeed, column (1) exhibits a significantly negative coefficient associated to the gender/project scale interaction term, while column (2) shows that the quadratic interaction term is significantly negative. The gender gap in loan size is thus increasing - linearly at best, quadratically at worse - with the project scope.

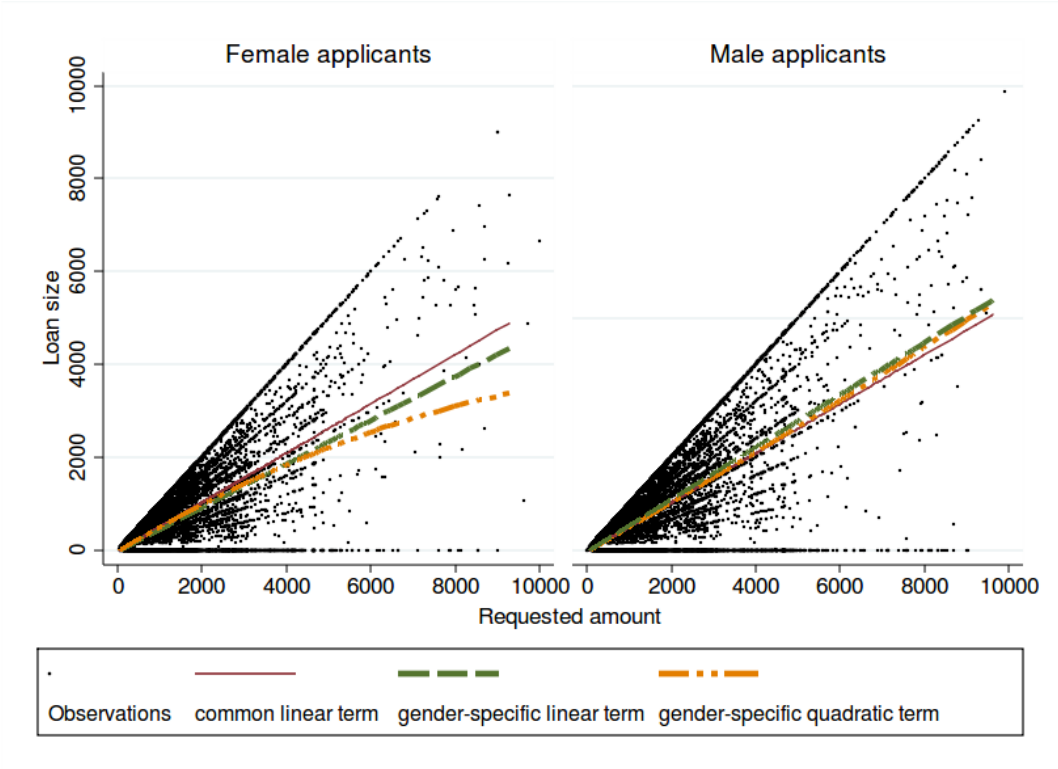
Figure 1 illustrates the regression results. Each graph represents the gender-specific loan sizes as functions of the requested amounts. The dashed lines, respectively curves, are the linear, respectively quadratic, trends of the gender-specific slope regressions. The thin continuous line is the aggregate linear trend (from eq.13) provided as a benchmark. Figure 1 shows that both specifications offer reasonable pictures of the scatter plot.

Figure 1 also confirms that the quadratic specification produces a stronger glass ceiling effect. For example, for a BRL 8,000 request (which is high according to VivaCred's standards), the gender-specific linear specification predicts an average loan size difference of BRL 1,238 between male and female borrowers whereas the quadratic specification predicts a BRL 1,939 difference.

A robustness check for the glass-ceiling effect is performed by splitting the full sample in two subsamples according to the requested amount (with the

[16] The coefficients of the control variables (including the loan officer's gender) are similar to those given in table 4. Hence, we do not report them here.

Figure 1: The linear and quadratic glass ceiling effects



cut-off at the mean),[17] and estimating eq.12 on two separate subsamples. Table 6 presents the results, together with a Chow test for equal coefficients in the two regressions.

For tiny requests, the gender gap in slopes is significant but extremely small (-0.0347). For small loans, the gender gap is significant, and eight times larger than for tiny loans (-0.230). Expectedly, these coefficients are significantly different from each other. Overall, the results confirm the presence of a glass ceiling, and highlight that the loan size depends in a non-linear (concave) fashion on the requested amount.

The glass-ceiling effect in loan size is thus a robust feature. The source of this puzzling evidence remains unclear, though. Why do loan officers impose too tough credit rationing to borrowers who would otherwise be more profitable? When economic arguments fall short of explaining the facts, behavioral explanations sometimes provide clues. In particular, our findings are consistent with loan officers being subject to gender stereotyping. Due to

[17] As the mean requested amount is BRL 1014, or approximately USD 576, we refer to the corresponding loans as "tiny" and "small".

Table 6: Glass-ceiling effect: Two subsamples

	Loan size		
	(1)	(2)	
Subsample:[a]	Tiny requests	Small requests	Differences in coefficients
Female applicant (F)	-79.86***	66.32***	***
	(7.74)	(18.39)	
RRA	0.489***	0.670***	***
	(0.0079)	(0.0085)	
RRA * F	-0.0347***	-0.230***	***
	(0.0113)	(0.0141)	
Observations	20,804	13,046	
R-squared	0.525	0.672	

[a]Cut-off at the mean requested amount: BRL 1,392.
Standard errors in parentheses; *** p<0.01.
Same controls as in table 4, col. (4)- (5).

decentralization, microcredit officers benefit from extensive leeway in their everyday work, which means that the information asymmetry between the MFI and its agents may be huge. Moreover, unlike US banks, MFIs in developing countries are mostly unregulated, in particular with regard to discriminatory practices.

However, we cannot fully exclude the possibility that real differences in creditworthiness do exist between male and female applicants, and that loan officers capture such differences through soft information unreported to the MFI. Indeed, the gender differences in entrepreneurial characteristics and performances in developed countries are debated in the literature and the evidence of discrimination remains controversial. For instance, Sexton and Bowman-Upton (1990) exhibit gender-related managerial differences, notably in risk aversion, but these authors find that these differences are largely overweighted as a basis for gender stereotyping. On the opposite, using Canadian data Haines et al. (1999) claim that "borrower attributes and terms of lending do not vary by gender of borrower" (p.291). Strikingly, even when gender discrimination is accounted for, this discrimination seems to have little impact on the chances of success of female-owned small businesses (Fischer et al., 1993), perhaps because women make a better use of their social capital (Carter et al., 2003).

In fact, the characteristics of female micro-entrepreneurs in developing countries remain largely unexplored. Thanks mainly to the emergence of microfinance, authors have started investigating the poor's financial life (Collins et al., 2009), and in particular the poor women's everyday struggle to ensure their household's basic needs (Guérin, 2011). Still, much more needs

to be done to better understand - and act on - the gender inequalities that plague the economic activity in developing countries. In that line, our results confirm the findings by, e.g., Johnson (2004) and Corsi et al. (2006) that a gender-sensitive approach makes sense in the microfinance industry.

6 Conclusion

Combining gender stereotyping and pure prejudice, our theoretical model shows that disparate treatment in loan allocation may take different forms. The empirical analysis performed on data from a Brazilian MFI reveals that the loan approval rate is gender-neutral, but there is a glass-ceiling in loan size that hurts the women entrepreneurs with the largest projects.

Actually, such a biased loan allocation is detrimental not only to the applicants who suffer from discrimination, but also to the lending institution that misses profit opportunities because of its agent's bias. In microfinance though, no systematic investigation for biased loan allocation has been put in place yet, nor than has any regulation. Supposedly, the social orientation of most MFIs could act as a natural prevention device against discriminatory practices. However, as emphasized by Labie et al. (2010), internal governance tools, like monitoring and wage incentives, may fall short when it comes to eradicate discrimination, mainly because of financial constraints.[18] There is therefore room for external actors, like donors and regulatory authorities, to come up with an anti-discrimination agenda.

Our results also raise concern on two apparently benign assumptions commonly made in the microfinance literature. Firstly, authors often use the gender dummy as a proxy for poverty. In fact, doing so results in both mixing up poverty and gender bias, and ignoring gender differences in loan requests for similar poverty levels.

Secondly and more importantly, academics and practitioners routinely use average loan size as an assessment tool for MFIs' social mission fulfillment. However, on top of being abusively penalizing for cross-subsidization and progressive lending (Armendáriz and Szafarz, 2011), unconditional average loan size is manipulable through disparate treatment of some clientele segments, like women and discriminated-against minorities. Therefore, average loan size not only is a poor indicator (Dunford, 2002), but also drives perverse incentives. Opportunistic MFI managers whose funding is conditioned by low

[18] Aubert et al. (2009) also argue that giving incentives is costly in pro-poor MFIs.

average loan size could indeed let their loan officers exert credit rationing through discrimination, as emphasized in this paper.

In the wake of the recent financial crisis, the gender-specific attitudes of bankers have attracted increased interest. In that line, a side output of our study concerns the impact of the officer's gender on the loan allocation process. Firstly, we have shown that the glass ceiling effect is evidenced irrespective of the loan officer's gender. Hence, our findings do not support the "gender affinity" hypothesis in the spirit of the "cultural affinity" theory tested in the mortgage lending industry (Hunter and Walker, 1996; Bostic, 2003). Secondly, we have observed that female loan officers are tougher than their male colleagues both in loan granting and in loan size determination.

Fully elucidating why female and male officers adopt diverging screening methodologies goes beyond the scope of this paper. However, psychological factors linked to risk assessment are likely involved (Borghans et al., 2009). Such factors could also explain why female applicants request smaller loans than their male counterparts with similar characteristics. Alternatively, it could be that female borrowers refrain from requesting loan sizes that would put at risk their financial situation within their household. Such a rationale would be in line with the findings that microcredit increases women's financial vulnerability (Goetz and Sen Gupta, 1996; Garikipati, 2008; Guérin et al., 2009).

Gender stereotyping is observed in a wide variety of situations, including small-business lending (Weller, 2009). Therefore, the absence of a gender gap in loan approval rate is a remarkable accomplishment for VivraCred, the MFI under scrutiny in this paper. Further studies are, however, needed to assess whether our results also apply to other MFIs, in particular the ones that claim to be committed to women empowerment. Additionally, our results should encourage regulators, donors, and other recommendation issuers to favor the release of disaggregated data by MFIs. Aggregate data (like the percentage of women served by the MFI) are blatantly insufficient to detect disparate treatment.

Further work could also examine the impact of gender on creditworthiness through default history (Ferguson and Peters, 1997), and check whether gender interacts with any creditworthiness characteristics. If women do indeed exhibit lower default rates, as often claimed by the microcredit industry and confirmed by Marrez and Schmit (2009) on Moroccan data, then the presence of taste-based discrimination, as opposed to profit-based statistical discrimination, would become undeniable.

Viewed through the women empowerment lens, our results are consistent with

two dominant, but seemingly contradictory, statements made in the literature. On the one hand, the fact that access to credit is gender-blind confirms that microcredit offers unexplored opportunities to female entrepreneurs. But on the other hand, women keep facing harsher conditions than men regarding not only their social and familial statuses, but also their borrowing possibilities. In this perspective, our results extend to credit conditions the mixed conclusions on women empowerment reached by Kabeer (2001).

Lastly, the scope of this paper goes beyond microcredit and gender issues. While the current literature is mostly focused on loan denial rates, this paper demonstrates that examining loan sizes may reveal insightful as well. Having a loan approved is good news for an entrepreneur, but when it comes to business purposes, loan size matters also.

Acknowledgements

The authors thank Juliano Assunção, Marcella Corsi, Bert d'Espalier, Isabelle Guérin, Valentina Hartaska, Marek Hudon, Marc Labie, Anaïs Périlleux, Koen Rossel-Cambier, Jean-Michel Servet, Øystein Strøm, Rodrigo Soares, and the participants to the *Third International Workshop on Microfiance* (Groningen, August 2010) and of the *Canadian Economic Association Annual Meeting* (Ottawa, May 2010) for helpful discussions and suggestions. Isabelle Agier is grateful to Capes, Faperj (Brazil), and Région Ile de France (France) for financial support.

References

Alesina, Alberto F., Francesca Lotti, and Paolo Emilio Mistrulli. 2008. "Do Women Pay More for Credit? Evidence from Italy." National Bureau of Economic Research Working Paper Series 14202.

Armendáriz, Beatriz, and Ariane Szafarz. 2011. "On Mission Drift In Microfinance Institutions." In *The Handbook of Microfinance*, 341–366. London-Singapore, B. Armendariz and M. Labie (Eds):World Scientific Publishing.

Armendáriz, Beatriz, and Jonathan Morduch. 2010. *The Economics of Microfinance.* 2 ed. Cambridge, MA:The MIT Press.

Aubert, Cécile, Alain de Janvry, and Elisabeth Sadoulet. 2009. "Designing Credit Agent Incentives to Prevent Mission Drift in pro-poor Microfinance Institutions." *Journal of Development Economics*, 90(1): 153–162.

Becker, Gary S. 1971. *The Economics of Discrimination.* 2nd ed. Chicago, IL:University of Chicago Press.

Bellucci, Andrea, Alexander Borisov, and Alberto Zazzaro. 2010. "Does Gender Matter in Bank-firm Relationships? Evidence from Small Business Lending." *Journal of Banking & Finance*, 34(12): 2968–2984.

Blanchard, Lloyd, Bo Zhao, and John Yinger. 2008. "Do Lenders Discriminate Against Minority and Woman Entrepreneurs?" *Journal of Urban Economics*, 63(2): 467–497.

Blanchflower, David G., Phillip B. Levine, and David J. Zimmerman. 2003. "Discrimination in the Small-Business Credit Market." *Review of Economics and Statistics*, 85(4): 930–943.

Borghans, Lex, Bart Golsteyn, James J. Heckman, and Huub Meijers. 2009. "Gender Differences in Risk Aversion and Ambiguity Aversion." IZA Discussion Paper 3985.

Bostic, Raphael. 2003. "A Test of Cultural Affinity in Home Mortgage Lending." *Journal of Financial Services Research*, 23(2): 89–112.

Buttner, E. Holly, and Benson Rosen. 1988. "Bank Loan Officers' Perceptions of the Characteristics of Men, Women, and Successful Entrepreneurs." *Journal of Business Venturing*, 3(3): 249–258.

Buvinic, Mayra, and Marguerite Berger. 1990. "Sex Differences in Access to a Small Enterprise Development Fund in Peru." *World Development*, 18(5): 695–705.

Carter, Nancy, Candida Brush, Patricia Greene, Elizabeth Gatewood, and Myra Hart. 2003. "Women Entrepreneurs who Break Through to Equity Financing: the Influence of Human, Social and Financial Capital." *Venture Capital: An International Journal of Entrepreneurial Finance*, 5(1): 1–28.

Cavalluzzo, Ken, and John Wolken. 2005. "Small Business Loan Turndowns, Personal Wealth, and Discrimination." *Journal of Business*, 78(6): 2153–2178.

Cavalluzzo, Ken, and Linda Cavalluzzo. 1998. "Market Structure and Discrimination: The Case of Small Businesses." *Journal of Money, Credit and Banking*, 30(4): 771–92.

Collins, Daryl, Jonathan Morduch, Stuart Rutherford, and Orlanda Ruthven. 2009. *Portfolios of the Poor: How the World's Poor Live on $2 a Day.* Princeton:Princeton University Press.

Corsi, Marcella, Fabrizio Botti, Tommaso Rondinella, and Giulia Zacchia. 2006. "Women and Microfinance in Mediterranean Countries." *Development*, 49(2): 67–74.

Daley-Harris, Sam. 2009. "State of the Microcredit Summit Campaign Report." Microcredit Summit Campaign, Washington, D.C.

Dunford, Christopher. 2002. "What's Wrong with Loan Size?" Freedom from Hunger Discussion paper, Davis, CA.

Fajnzylber, Pablo, William F. Maloney, and Gabriel V. Montes-Rojas. 2011. "Does Formality Improve Micro-firm Performance? Evidence from the Brazilian SIMPLES Program." *Journal of Development Economics*, 94(2): 262–276.

Fein, S, and S.J. Spencer. 1997. "Prejudice as Self-Image Maintenance: Affirming the Self Through Derogating Others." *Journal of Personality and Social Psychology*, 73: 44, 31.

Ferguson, Michael F., and Stephen R. Peters. 1997. "Cultural Affinity and Lending Discrimination: The Impact of Underwriting Errors and Credit Risk Distribution on Applicant Denial Rates." *Journal of Financial Services Research*, 11(1): 153–168.

Ferreira, Francisco H.G., Phillippe G. Leite, and Martin Ravallion. 2010. "Poverty Reduction without Economic Growth?: Explaining Brazil's Poverty Dynamics, 1985-2004." *Journal of Development Economics*, 93(1): 20–36.

Fischer, Eileen M., A. Rebecca Reuber, and Lorraine S. Dyke. 1993. "A Theoretical Overview and Extension of Research on Sex, Gender, and Entrepreneurship." *Journal of Business Venturing*, 8(2): 151–168.

Fletschner, Diana. 2009. "Rural Women's Access to Credit: Market Imperfections and Intrahousehold Dynamics." *World Development*, 37(3): 618–631.

Garikipati, Supriya. 2008. "The Impact of Lending to Women on Household Vulnerability and Women's Empowerment: Evidence from India." *World Development*, 36(12): 2620–2642.

Goetz, Anne Marie, and Rina Sen Gupta. 1996. "Who takes the credit? Gender, power, and control over loan use in rural credit programs in Bangladesh." *World Development*, 24(1): 45–63.

Guérin, Isabelle. 2011. "The Gender of Finance and Lessons for Microfinance." In *The Handbook of Microfinance*, 589–612. London-Singapore, B. Armendariz and M. Labie (Eds):World Scientific Publishing.

Guérin, Isabelle, Marc Roesch, Venkatasubramanian, Mariam Sangare, and Santosh Kumar. 2009. "Microfinance and the Dynamics of Financial Vulnerability. Lessons from Rural South India." RuMe Working Paper.

Haines, G.H., B.J. Orser, and A.L. Riding. 1999. "Myths and Realities: An Empirical Study of Banks and the Gender of Small Business Clients." *Canadian Journal of Administrative Sciences / Revue Canadienne des Sciences de l'Administration*, 16(4): 291–307.

Han, Song. 2004. "Discrimination in Lending: Theory and Evidence." *Journal of Real Estate Finance and Economics*, 29(1): 5–46.

Helland, Inge S. 1990. "Partial Least Squares Regression and Statistical Models." *Scandinavian Journal of Statistics*, 17(2): 97–114.

Hudon, Marek. 2009. "Should Access to Credit be a Right?" *Journal of Business Ethics*, 84(1): 17–28.

Hunter, William C, and Mary Beth Walker. 1996. "The Cultural Affinity Hypothesis and Mortgage Lending Decisions." *Journal of Real Estate Finance and Economics*, 13(1): 57–70.

ILO. 2009. "Small Change, Big Changes: Women and Microfinance." International Labour Organization, Geneva.

Johnson, Susan. 2004. "Gender Norms in Financial Markets: Evidence from Kenya." *World Development*, 32(8): 1355–1374.

Kabeer, Naila. 2001. "Conflicts Over Credit: Re-Evaluating the Empowerment Potential of Loans to Women in Rural Bangladesh." *World Development*, 29(1): 63–84.

Kunda, Ziva, and Lisa Sinclair. 1999. "Motivated Reasoning with Stereotypes: Activation, Application, and Inhibition." *Psychological Inquiry*, 10(1): 12–22.

Labie, Marc, Pierre-Guillaume Méon, Roy Mersland, and Ariane Szafarz. 2010. "Discrimination by Microcredit Officers: Theory and Evidence on Disability in Uganda." Université Libre de Bruxelles CEB Working Papers 10-007.

Lacour-Little, Michael. 1999. "Discrimination in Mortgage Lending: A Critical Review of the Literature." *Journal of Real Estate Literature*, 7(1): 15–50.

Ladd, Helen F. 1998. "Evidence on Discrimination in Mortgage Lending." *Journal of Economic Perspectives*, 12(2): 41–62.

Marrez, Helena, and Mathias Schmit. 2009. "Credit risk analysis in microcredit: How does gender matter?" Université Libre de Bruxelles CEB Working Papers 09-053.

Mayoux, Linda. 2002. "Microfinance and Women's Empowerment: Rethinking Best Practice." *Development Bulletin*, 57: 76–81.

Méon, Pierre-Guillaume, and Ariane Szafarz. 2011. "The Modern Corporation as a Safe Haven for Taste-based Discrimination: An Agency Model of Hiring Decisions." *Labour Economics*, 18(4): 487–497.

Morduch, Jonathan. 1999. "The Microfinance Promise." *Journal of Economic Literature*, 37(4): 1569–1614.

Munnell, Alicia H., Geoffrey M. B. Tootell, Lynn E. Browne, and James McEneaney. 1996. "Mortgage Lending in Boston: Interpreting HMDA Data." *American Economic Review*, 86(1): 25–53.

Ross, Stephen L. 2000. "Mortgage Lending, Sample Selection and Default." *Real Estate Economics*, 28(4): 581–621.

Ross, Stephen L, and John Yinger. 1999. "Other Evidence of Discrimination: Recent Studies of Redlining and of Discrimination in Loan Approval and Loan Terms." In *Mortgage Lending Discrimination: A Review of Existing Discrimination*, Margery Austin Turner, Felicity Skidmore ed., 17–42. Washington, D.C.:The Urban Institute.

Schafer, Robert, and Helen F Ladd. 1982. *Discrimination in Mortgage Lending.* Cambridge, MA:MIT Press.

Sexton, Donald L., and Nancy Bowman-Upton. 1990. "Female and Male Entrepreneurs: Psychological Characteristics and their Role in Gender-related Discrimination." *Journal of Business Venturing*, 5(1): 29–36.

Sheriff, Robin E. 2000. "Exposing Silence as Cultural Censorship: A Brazilian Case." *American Anthropologist*, 102(1): 114–132.

Stiglitz, Joseph E, and Andrew Weiss. 1981. "Credit Rationing in Markets with Imperfect Information." *American Economic Review*, 71(3): 393–410.

Storey, D. 2004. "Racial and Gender Discrimination in the Micro Firms Credit Market?: Evidence from Trinidad and Tobago." *Small Business Economics*, 23(5): 401–422.

Tenenhaus, M. 1998. *La Régression PLS: Théorie et Pratique.* Paris:Technip.

Weller, Christian E. 2009. "Credit Access, the Costs of Credit and Credit Market Discrimination." *Review of Black Political Economy*, 36(1): 7–28.

Wold, S., A. Ruhe, H. Wold, and W. J. Dunn. 1984. "The Collinearity Problem in Linear Regression. The Partial Least Squares (PLS) Approach to Generalized Inverses." *SIAM Journal on Scientific and Statistical Computing*, 5(3): 735–743.