6 Is There a Glass Ceiling in Loan Size for female borrower?

with Ariane Szafarz

6.1 Introduction

The literature on discrimination appeared with Gary Becker seminal work (Becker (1971)). The distinction made between statistical discrimination (economically justified) and taste-based discrimination, initially presented in the labor market, can be applied in other fields like the credit market (Berkovec et al. (1994)).

Statistical discrimination in lending occurs when a lender can not observe the applicant creditworthiness but knows that the group he belongs has a lower average creditworthiness (at least on the lender's evaluation) than another group. Thus, the loan applicant receive bad credit conditions (denial, rationing, interest rate or collateral requirement) because of this group membership. In this case, group-specific treatment is not due to lender dislike but caused by information asymmetry. On the contrary, taste-based discrimination is purely due to social preferences: the lender has prejudices against one group members.

In the labor market case, taste-based discrimination (willingness to pay in order to avoid dealing with the disliked group) is measured by the wage difference between two equally skilled workers from the two different groups. As credit market deals with risk level, this measurement is more complex. When group-specific credit condition are based on the interest rate, the two kinds of discrimination are indistinguishable: differentiated interest rate can be the cause or the consequence of the difference in repayment behavior between the two groups. When an MFI apply a flat interest rate (as Vivacred do), potentially disparate credit conditions lies on loan approval and loan size. The previous chapter provides evidences advocating for taste-based discrimination. Thus, this chapter explores the consequences of taste-based discrimination on credit conditions by introducing explicitly an additional cost of lending to a discriminated against group member.

The theoretical model shows that Beckerian (taste-based) gender discrimination may lead to three types of lender behavior depending on its distaste intensity: 1) denial of all female applications, 2) unfair downsizing of the highest female requested loans only, and 3) no impact. Given the evidence that microfinance institutions serve a large proportion of women, the first case is discard in this industry. Therefore, the empirics are devoted to checking whether scenario 2) is observed in practice, or not.

The literature on discrimination in lending is traditionally focused on denial. This binary approach is partially due to a lack of continuous information and sometimes to market segment specificities. For example, a mortgage loan, is entirely approved or denied. Fortunately, continuous information (loan size), provided by Vivacred, allows to go deeper and to test the different theoretical scenario.

Chapter 4, exhibits a gender-gap in loan size beyond the difference of requested amount. Women face harder loan conditions than men do. In the empirical part of this chapter, we follow the same methodological path (PLS) and includes a quadratic term in order to capture the non-linearity. We are able to confirm the second case predicted by the model: the most able women face the highest penalty. Then, this glass ceiling endured by female entrepreneurs, is shown not to be economically justified. The results are consistent with the mitigated conclusions reached by the literature on women empowerment through microfinance (Kabeer (2001)).

According to chapter 3, the credit officer's ability is important especially for clients' selection. Furthermore, chapter 5 reveals that the officer's gender is relevant for loan size and repayment. If taste-based discrimination is at stake, one could expect a difference of gender-gap intensity depending on credit officer's gender. Female credit officers could reduce or eliminate such a gap. In the second part of this chapter, we examine first, whether credit officer's gender matters for gender-gap in loan size and second, whether the glass ceiling appears with the same magnitude for loans attended by male and female officers.

We found a compensation from female credit officers to female clients only for small loans. Considering large loans, female clients downscaling is stronger from female officers than from their male counterparts. This result is in accordance with Borghans et al. (2009) survey on financial psychology: woman are more risk adverse both in their personal and professional life which includes business activities and decision making as a bank manager, for example.

The paper is organized as follows. Section 6.2 presents the theoretical model à la Becker. The existence of a glass ceiling in loan size is studied in section 6.3 and its lack of economic foundation in section 6.3.1. Section 6.4 examines the behavior of male and female credit officers regarding the borrower's gender and requested amount. Section 6.5 concludes.

6.2 The Model

The population of potential borrowers is denoted by P. Each candidate $(x, g) \in P$ is characterized by the observable vector x including all variables relevant to assess the candidate's creditworthiness[1], and the gender characteristic, $g \in \{F, M\}$, assumed independent from creditworthiness. As a consequence, only the x components should be relevant to a discrimination-blind loan officer. However, we assume that those officers are biased against female applicants $(g = F)$.

The model has one period and, as illustrated by the case of Vivacred, the microfinance institution presented in Section 4.2, all loans are offered with the same interest rate[2] r. At time 0, the risk-neutral credit officer receives a loan request from applicant (x, g), and subsequently attributes him/her a loan of size $B = B(x, g)$ (equal to zero, in case of denial) by maximizing expected profit,$E\left[W\left(x, g\right)\right]$, which equals expected future reimbursement minus costs. The costs include: 1) the MFI cost of capital $r_0 < r$, and 2) the prejudiced agent's psychological cost associated to serving women: $\delta(g)$, with $\delta(M) = 0$ and $\delta(F) = \delta \in [0, 1]$. The credit officer maximization problem reads:

$$\underset{B \geqslant 0}{Max}\, E[W(x, g)] = E[R(B, x)] - B(1 + r_0 + \delta(g)) \tag{6-1}$$

where $R(B, x)$ is the stochastic gender-independent reimbursement from client (x, g) for a loan of size B, and $E[.]$ represents the expectation operator. Given the objective function in equation (6-1), a client (x, F) is likely to receive a smaller loan than client (x, M) because she needs to be more profitable to compensate for the cost penalty resulting from the officer's bias.

[1] All characteristics relevant to assess creditworthiness are assumed observable, implying that discrimination is taste-based only.

[2] This is a common practice in microcredit institutions. However, the lending rate could alternatively be adjusted to the client's risk characteristics in x, but besides making the model more complicated, this would not affect much the results.

At time 1, the client reimburses the loan according his/her financial possibilities that depends on available revenue coming from his/her business activity. We assume the existence of a penalty sufficiently high to deter strategic default[3]. The revenue in period 1, denoted by y, is stochastic. For 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 is characterized by a probability $y(x)$ to generate the low value $\underline{y}$ in the following way[4]:

$$y(x,g) = y(x) = \begin{cases} \underline{y} \text{ with probability } \pi(x) \\ \overline{y} \text{ with probability } 1-\pi(x) \end{cases} \tag{6-2}$$

At time 1, the random variable $y(x)$ realizes and the corresponding borrower (x,g) reimburses $R(B,x)$, that is as much as he/she can, given the situation:

$$R(B,x) = \min\{y(x), B(1+r)\} \tag{6-3}$$

Table 1 summarizes the six reimbursement possibilities depending on the outstanding loan size B and the client's realized revenue ($\underline{y}$ or $\overline{y}$).The reimbursement is deterministic for small loans ($B \leq \frac{\underline{y}}{1+r}$), and stochastic otherwise.

Table 6.1: The reimbursement $R(B,x)$ depending on B and y.

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

The model is solved by backward induction. From Table 1, we derive the reimbursement expected at time 0:

$$E[R(B,x)] = \begin{cases} B(1+r) & \text{if} \quad B \leq \frac{\underline{y}}{1+r} \\ \pi(x)\underline{y} + (1-\pi(x))B(1+r) & \text{if} \quad \frac{\underline{y}}{1+r} < B < \frac{\overline{y}}{1+r} \\ \pi(x)\underline{y} + (1-\pi(x))\overline{y} & \text{if} \quad B \geq \frac{\overline{y}}{1+r} \end{cases} \tag{6-4}$$

Given the client's reaction function, the officer's objective function writes:

[3]Default in Vivacred implies that the client is nationally publicized as a bad risk.

[4]Parametrizing the clients according to their probability to generate low revenue is a convenient way to make expected reimbursement continuous with respect to creditworthiness. In practice, the loans are reimbursed by installments, with makes realistic the possibility of partial repayment. Indeed, the expected reimbursement ,$E[R(B,x)]$, is to be interpreted as the expected present value of all future payments made by the client in relation with the loan at stake.

$$E\left[W(x,g)\right] = \begin{cases} B(r - r_0 - \delta(g)) & \text{if} \quad B \leq \frac{\underline{y}}{1+r} \\ \pi(x)\underline{y} + B[r - r\pi(x) - \pi(x) - r_0 - \delta(g)] & \text{if} \quad \frac{\underline{y}}{1+r} < B < \frac{\overline{y}}{1+r} \\ \pi(x)\underline{y} + (1 - \pi(x))\overline{y} - B(1 + r_0 + \delta(g)) & \text{if} \quad B \geq \frac{\overline{y}}{1+r} \end{cases} \tag{6-5}$$

Three notable consequences are drawn from (6-5). First, if the agent's prejudice is strong enough to yield $r_0 + \delta(g) > r$, then no F applicant will ever get a loan, whatever her creditworthiness. Second, no loan size is larger than $\frac{\overline{y}}{1+r}$, because reimbursement is capped by $\overline{y}$. Third, as the officer's objective function is continuous and piecewise linear (see figure 6.1), only three optimal values are possible for B: 0 (no loan) $\underline{B} = \frac{\underline{y}}{1+r}$ (small loan), and $\overline{B} = \frac{\overline{y}}{1+r}$ (larger loan). Therefore, to solve the officer maximization problem, we only need to compare the three corresponding values for $E\left[W(x,g)\right]$. Consequently, equation 6-5 simplifies to:

$$E\left[W(x,g)\right] = \begin{cases} 0 & \text{if} \quad B = 0 \\ \underline{B}[r - r_0 - \delta(g)] & \text{if} \quad B = \underline{B} \\ \pi(x)(1+r)[\underline{B} - \overline{B}] + \overline{B}[r - r_0 - \delta(g)] & \text{if} \quad B = \overline{B} \end{cases} \tag{6-6}$$

The optimal loan size, B^*, is thus given by:

$$B^*(x,g) = \begin{cases} 0 & \text{if} \quad r - r_0 - \delta(g) < 0 \\ \underline{B} & \text{if} \quad \pi(x)(1+r) > r - r_0 - \delta(g) \geq 0 \\ \overline{B} & \text{if} \quad \pi(x)(1+r) \leq r - r_0 - \delta(g) \end{cases} \tag{6-7}$$

As $\delta(M) = 0$ and $r > r_0$, the M candidates receive at least $\underline{B}$. Only the F applicants can face denial.

The optimal loan size for an M applicant is given by:

$$B^*(x,M) = \begin{cases} \underline{B} & \text{if} \quad \pi(x) > \frac{r - r_0}{1+r} \\ \overline{B} & \text{if} \quad \pi(x) \leq \frac{r - r_0}{1+r} \end{cases} \tag{6-8}$$

Regarding F clients, two situations may arise. First, if the prejudice is so high that $\delta > r - r_0$, then all female applicants face denial. Second, if $\delta \leq r - r_0$, then the prejudice acts as an additional probability[5] of low revenue. Let us define:

$$\tilde{\pi}(x) = \pi(x) + \frac{\delta}{1+r} \tag{6-9}$$

Then, the optimal loan size for an F applicant is:

[5] Actually, this number is no more a probability as it may exceed one.

$$B^*(x,F) = \begin{cases} 0 & \text{if} \quad \delta > r - r_0 \\ \underline{B} & \text{if} \quad \delta \le r - r_0 \text{ and } \tilde{\pi}(x) > \frac{r-r_0}{1+r} \\ \overline{B} & \text{if} \quad \delta \le r - r_0 \text{ and } \tilde{\pi}(x) \le \frac{r-r_0}{1+r} \end{cases} \tag{6-10}$$

The F candidates are not all penalized to the same extent. The actual harm depends on the applicant's probability to generate high revenue $(1 - \pi(x))$, and on the officer's level of bigotry (δ). Table 2 summarizes the situation.

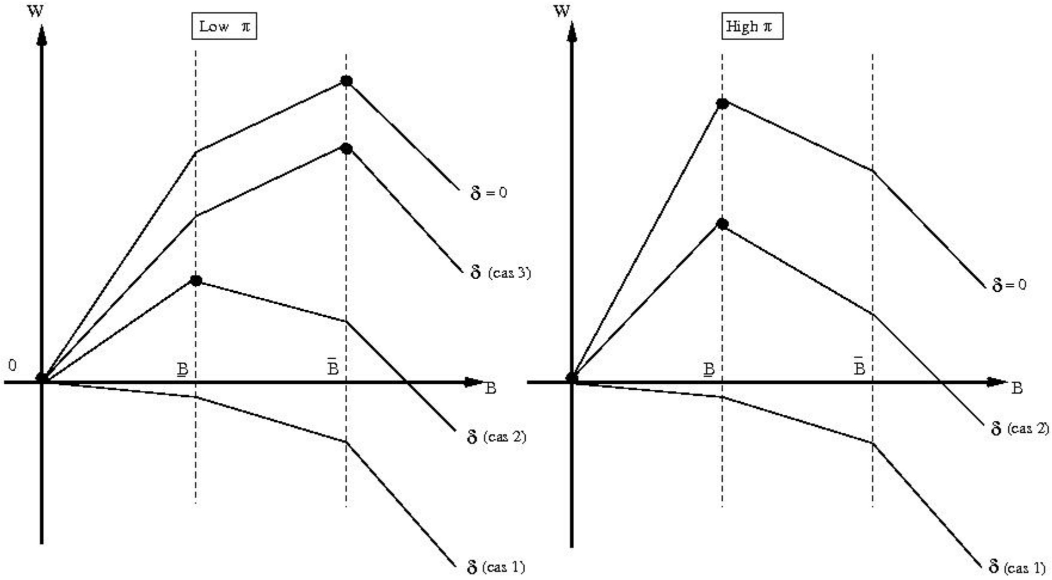
Table 6.2: Optimal loan size for F candidates according to their probability of generating low revenues $(\pi(x))$ and the officer's prejudice(δ)

Officer's δ		**Applicant's $\pi(x)$**	
		More able F candidate: $\pi(x) \le \frac{r-r_0}{1+r}$	**Less able F candidate:** $\pi(x) > \frac{r-r_0}{1+r}$
Case 0:	$\delta = 0$ No prejudice	$B^* = \overline{B}$	$B^* = \underline{B}$
Case 1:	$\delta \le r - r_0$ and $\frac{\delta}{1+r} \le \frac{r-r_0}{1+r} - \pi(x)$	*No Discrimination* $B^* = \overline{B}$	Impossible
Case 2:	$\delta \le r - r_0$ and $\frac{\delta}{1+r} > \frac{r-r_0}{1+r} - \pi(x)$	*Loan downscaling* $B^* = \underline{B}$	*No Discrimination* $B^* = \underline{B}$
Case 3:	$\delta > r - r_0$	*Discriminatory denial* $B^* = 0$	

If $\delta = 0$, the F candidates are not discriminated against and they get the same loan size as their M counterpart. If $\delta < r - r_0$ (case 1) and the F candidate appears very profitable (small probability of low revenue: $\pi(x) \le \frac{r-r_0-\delta}{1+r}$), the credit officer's bigotry does not affect loan size. On the opposite, if $\delta \ge r - r_0$ (case 3), the loan application is denied whatever the candidate's profitability. In the middle scenario (case 2), the credit officer prejudice is small enough $(\delta < r - r_0)$ to avoid discriminatory denial but high enough $(\pi(x) + \frac{\delta}{1+r} > \frac{r-r_0}{1+r})$ to prevent the F applicant from getting $\overline{B}$. This is the typical downsizing situation (loan size equals to $\underline{B}$ instead of $\overline{B}$). In this scenario, a less profitable F client is not affected by prejudice as she gets the same amount, $\underline{B}$ with and without discrimination.

As illustrated by figure 6.1, F candidates are subject to potential discrimination whatever their creditworthiness, but the probability is smaller for those who are more likely to default (graph on the right). Indeed, for such clients, the officer has two possibilities only: unfair denial or fair loan size. According to table 2, in the intermediate situation (case 2), fair loan size is still chosen. On the opposite, for the most able F clients (graph on the left), the fair loan size is $\overline{B}$, and credit rationing is chosen by the officer in the intermediate situation. Therefore, prejudiced officers are particularly detrimental to their institution as they tend to downsize the loans provided to its most profitable female clients.

Figure 6.1: Officer's objective function and optimal loan size for an F applicant



In summary, strong aversion toward the F group leads to denial as the credit officer's distaste is too high to be compensated by expected profits. When this distaste is less pronounced, a trade-off appears between the expected profits and the agent's psychological cost to serve an F candidate. As this cost is proportional to loan size, it is more detrimental to the most profitable candidates.

The case 2 situation translates into a "glass ceiling" effect. Indeed, in that case all female applicants who deserve a loan (their expected revenue is sufficient to avoid loan denial) end up with the same loan size $\underline{B}$ irrespectively to their ability to repay. In other words, no increase in the probability of high revenue will ever make it possible for a woman to reach the higher loan size $\overline{B}$, which therefore remains reserved to the most able male candidates. This situation thus corresponds to what is typically referred to as a "glass ceiling" effect.

This result contradicts the argument by Zycher & Wolfe (1994) stating that there is more room for lending discretion in the "gray area" where the applicant's qualification is not well established (in our case, this gray area corresponds to the parameters zone: $\pi(x) \simeq \frac{r-r_0}{1+r}$). This difference follows from the fact that our model imposes no penalty to rogue agents, which is in line with the current practice. Although incentive schemes are becoming commonly used by MFIs (McKim & Hughart (2005)), no penalty for discriminatory behavior has, to our knowledge, ever been enforced.

The result that the most able female clients are heavily penalized shows how detrimental taste-discrimination can be not only for the female clients, but also for the financial sustainability of the lending institution, which can lose profitable clients because of its agents' bigotry. In microfinance though, no systematic investigation for discrimination has been put in place yet, and there exist no regulation on that matter. However, the social orientation of most MFIs could act as a natural prevention mechanism to deter discriminatory practices provided that adequate monitoring instruments and/or incentives are put in place. Indeed, as shown from the survey data[6] reported by Labie et al. (2010), credit officers tend to be more biased than other MFI's employees. Unfortunately, Labie et al. (2010) also emphasize that due to cost issues, internal governance mechanisms may fall short in fully eliminating discrimination. Therefore, there is also room for external actors, like donors and regulatory authorities, to come up with an anti-discrimination agenda. But before drawing policy recommendation, a careful assessment of the facts is needed.

Chapter 4 shows that loan approval is not affected by the client's gender, but loan size determination is detrimental to female applicants. As a consequence, the results point in favor of the presence of gender prejudice but excludes the situation referred to as "case 1" (loan denial to female candidates) in the theoretical model. However, as the specification used for explaining loan size are linear, the presence of a glass-ceiling effect is difficult to assess. Non-linear specifications like those proposed in the next section are better suited for that purpose. Estimations are based on Vivacred database for which chapter 4 already provided description and descriptive statistics.

6.3 Glass ceiling in Loan Size for Women

The theoretical derivations in section 6.2 have demonstrated that a constant discriminatory bias from the credit officer does not produce a homogeneous effect on female borrowers. More specifically, the women who could generate larger benefits with larger loan are hurt more than the others. In order to assess this theoretical prediction, we now consider the possibility for non linearities in the loan size regression.

[6]The survey was about the treatment of disabled by MFIs in Uganda.

Chapter 4 has depicted (see eq. 4-5) a linear specification of the loan size on the requested amount with a *single slope* for both men and women. As non-linearity may take various forms, we consider alternatively two additional specifications here: gender-specific slopes and gender-specific quadratic shapes. Like in chapter 4, all regressions in this section are based on PLS estimation[7].

The first specification considers two gender-specific slopes through interaction terms between the gender dummy and the residual requested amount while sticking to linearity for each of them:

$$LS_i = c_F F_i + c_{RF}\, RRA_i F_i + c_{RM}\, RRA_i(1 - F_i) + \mathbf{c'_Z}\, \mathbf{Z_i} + \epsilon_i \tag{6-11}$$

with LS_i the loan size, F_i the female dummy, RRA_i the residual requested amount and $\mathbf{Z_i}$ the vector summarizing the controls for applicant i.

In that specification, the glass-ceiling effect would correspond to the case where c_{RF} is significantly smaller than c_{RM}. In that event, the difference between male and female applicants, with similar characteristics, is growing with the project scale (residual requested amount), which acts as a proxy for idiosyncratic expected revenue. Importantly, interaction variables are added to a specification already including the gender dummy (differentiating the ordinate at origin between male and female).

The second specification includes a single linear term but two gender-specific quadratic terms, allowing for a differenced concavity effect between genders:

$$LS_i = c_F F_i + c_R\, RRA_i + c_{QF}\, F_i (RRA_i)^2 + c_{QM}\, (1 - F_i)(RRA_i)^2 + \mathbf{c'_Z}\, \mathbf{Z_i} + \epsilon_i \tag{6-12}$$

A negative value for c_{QF} would capture the glass-ceiling effect according to which the women who request the largest loans are the most credit rationed.

[7]PLS regression including the residual requested amounts, and not the crude requested amounts. OLS regressions were also performed (results not reported). Interestingly, quadratic specification produced significant interaction terms and insignificant female dummy. Although this result is fully consistent with our theoretical findings, we prefer to concentrate on PLS regressions and avoid multicollinearity issues already treated in section 4.3.

Figure 6.2: Linear and quadratic adjustments for loan size

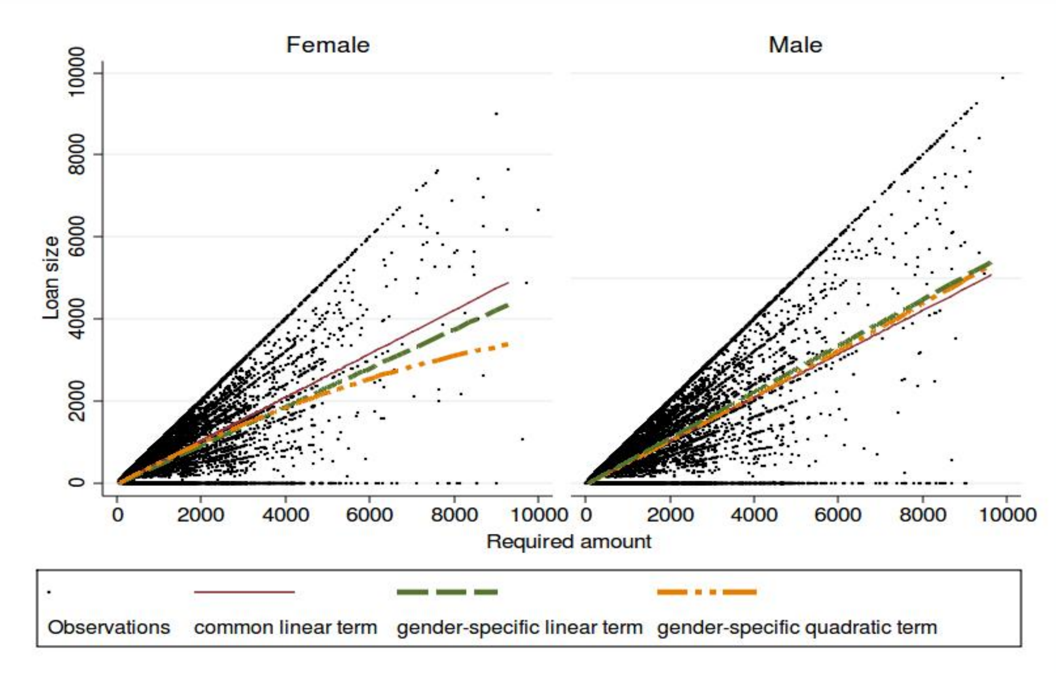


Table 6.3 depicts both specifications estimations and figure 6.2 illustrates the regression coefficients. Long-dashed lines are the gender-specific linear trends of the gender-specific slope regression. Thin continuous line is the common linear trend and dashed curves are the gender-specific quadratic evolution of quadratic specification. Figure 6.2 shows that both specifications (gender-specific slope and quadratic effect) offer reasonable pictures of the scatter plot.

Columns (1) and (2) in table 6.3 confirm the theoretical glass-ceiling prediction. Column (1) exhibits a smaller slope for women. As the two lines move away from each other, the gender gap in loan size is increasing with the requested amount.

Column (2) shows that the squared residual requested amount has a significantly negative impact when interacted with the female dummy and a positive impact when interacted with the male dummy. Compared to men with similar situations, women with bigger projects are more restricted. As the control variables are the same and the corresponding estimates look like those provided by table 4.3, we do not report them. Specifications (1) and (2) in table 6.3 have about the same explanatory power (R^2).

In eq.6-12, the requested amount stands as a proxy for business expected profits (corresponding to $(1 - \pi(x))$ in the theoretical model). For robustness

Table 6.3: Quadratic specifications (PLS only)

	Request		Collateral	
	(1)	(2)	(3)	(4)
Female client	-93.75***	-57.78***	-71.05***	-87.08***
	(5.758)	(5.912)	(6.644)	(5.846)
RRA		0.556***	0.573***	0.574***
		(0.00326)	(0.00280)	(0.00280)
RRA F	0.500***			
	(0.00461)			
RRA M	0.616***			
	(0.00351)			
RRA^2 F		-2.07e-05***		
		(1.47e-06)		
RRA^2 M		1.39e-05***		
		(6.61e-07)		
External income (EI)	0.327***	0.336***		0.409***
	(0.00765)	(0.00762)		(0.0104)
EI F			0.268***	
			(0.0115)	
EI M			0.373***	
			(0.0101)	
EI^2 F				-5.64e-05***
				(5.36e-06)
EI^2 M				-1.42e-05***
				(1.75e-06)
All controls	Yes	Yes	Yes	Yes
Observations	33850	33850	33850	33850
R-squared	0.731	0.733	0.728	0.729

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Financial values in deflated BRL (R$)

check, we perform the same estimation exercises with the household external income (columns (3) and (4) in table 6.3) leading to similar effects regarding gender-specific slopes. However, both quadratic terms in column (4) are negative meaning that, for all borrowers, the external income impact on loan size becomes proportionally smaller for higher income. Still, this effect is stronger when interacted with the female dummy than with male dummy.

Additionally, interpreting external income as a partial collateral, the results in column (3) show that, all other things being equal, female borrowers asking for larger loans need more collateral than men for the same requested amount. This could reflect the lender's knowledge that intra-household income allocation is favorable to men, making external revenue less relevant as a collateral for female borrowers. This view is consistent with the observation from the table 5.2 of chapter 4 that the guarantor's gender matters.

6.3.1 The Glass Ceiling is not Justified

Following chapter 5 methodology, we explore the potential economic justification of the glass ceiling phenomenon (increase of the gender-gap in loan size along the requested amount). We examine how male and female repayment behavior change along the loan size. The delay and default probability are estimated by probit regressions and the loss by a linear regression. Each regression takes in account a potential selection bias (Heckman procedure) induced by the committee approval or denial. Control variables are the same as in chapter 5. We regress the three repayment variables on the loan size (LS) and then on its interaction with the client's gender (LS*F and LS*(1-F)). Table 6.4 depicts the results and provides a test of coefficients comparison between genders.

Table 6.4: Repayment behavior along the loan size

	Delay (30 days)		Default (180 days)		Loss	
Fem. client	-0.0130***	-0.0168***	-0.00327***	-0.00208	-6.396***	-6.588***
	(0.00267)	(0.00391)	(0.000857)	(0.00132)	(1.752)	(2.515)
LS	-2.74e-05***		-7.76e-06***		-0.000549	
	(3.04e-06)		(1.22e-06)		(0.00193)	
LS*F		-2.48e-05***		-9.00e-06***		-0.000410
		(3.63e-06)		(1.58e-06)		(0.00235)
LS*(1-F)		-2.86e-05***		-7.40e-06***		-0.000601
		(3.19e-06)		(1.29e-06)		(0.00200)
RA	2.05e-05***	2.06e-05***	4.66e-06***	4.75e-06***	0.00642***	0.00641***
	(2.33e-06)	(2.34e-06)	(7.42e-07)	(7.70e-07)	(0.00159)	(0.00160)
Fem. officer	0.00929***	0.00932***	0.00182**	0.00179**	1.059	1.076
	(0.00293)	(0.00293)	(0.000864)	(0.000877)	(1.901)	(1.901)
Test: H0: LS*F = LS*(1-F)						
$\chi^2(1)$		1.74		1.43		0.01
$Prob > \chi^2$		0.1868		0.2312		0.9176
Observations	33530	33530	33530	33530	33530	33530

Heckman selection: loan approved; All controls of table 5.2 (chapter 5) are included here.
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Marginal effects at the mean reported for the probit.

According to chapter 5, delay and default probability decrease with the loan size when controlling for the requested amount (and all other observable characteristics). At first glance, this may seem counterintuitive. However, it can be rationalize by the use of cross-subsidization between the poorest and less poor clients (Stuart (2007)). Additionally, the loss is not changing along the loan size. Male and female clients behavior in the same way along the loan size in terms of repayment. None of the three repayment regressions (delay default and loss), show significant difference of loan size coefficient among genders. Thus, the repayment behavior evolve in the same way along the loan size for male and female clients.

In conclusion, there is no economic justification for intensifying the female loan downsizing for larger projects. For a same requested amount (and taking in account the committee approval), larger loans are more swiftly repaid independently from the client's gender. Female client are actually facing a glass ceiling as they are not able to get the same loan scale than their male counterpart when planning ambitious projects.

On one hand, chapter 4 depicts a significant responsibility of credit officers in the gender-gap, pointed out by gender-specific proposition to the credit committee. On the other hand, table 5.2 in chapter 5 reveals that the credit officer's gender significantly affects the loan size determination. Clients get smaller loans if attended by a female officer, independently from their gender. At the same time, a female client receive less than a men, independently from the credit officer's gender.

When discrimination is taste-based (as supported by empirical evidence of chapter 4 and 5 and assumed in the theoretical model in section 6.2), one could expect a difference in gender-gap between male and female credit officers. Thus, in the next section, we will examine if the glass ceiling amplitude depends on the credit officer's gender. We first, explore the difference of gender-gap between male and female credit officer in general (who penalize more female clients) and thus scrutinize this difference along the loan scale (is it related to the scale of the project).

6.4 Gender-Affinity between Clients and Officers?

In this section, we study whether the credit officer's gender interferes with the disparate treatment endured by female clients. Table 6.5 gives the contingency table linking the client's and officer's gender. Each combination roughly concerns one quarter of the loans. Nevertheless, the χ^2 independence test indicates that credit officers deal significantly more with same-sex clients[8].

Table 6.5: Loan repartition in client and credit officer gender

%	Female client	Male client	Total (clients)
Female c.o.	24.29	23.12	47.41
Male c.o.	25.31	27.28	52.59
Total (officers)	49.60	50.40	100.00

[8]Pearson $\chi^2(1) = 33.6798$ and P-value = 0.000. This effect is surprising given that, in Vivacred, each credit officer has a specific geographic area to serve. Nonetheless, female credit officers may be allocated to areas that exhibit a higher concentration of female businesses.

Table 6.6 depicts the portfolio composition of male and female credit officers. Although applicants request, on average, the same amount (BRL 1378) to male and female credit officer, clients attended by female officers get smaller loans (BRL 977 against BRL 1049)[9]. Despite differentiated loan sizes, the number of installments is about the same.

Table 6.6: Portfolio comparison among credit officer's gender

	All applications			Approved loans		
Credit Officers	Female	Male	diff	Female	Male	diff
Female Applicant	0.512	0.480	0.0317***	0.512	0.481	0.0311***
Requested Amount	1395.7	1380.2	15.43	1379.7	1377.9	1.865
Proposed Amount	999.0	1065.3	-66.31***	1011.5	1075.9	-64.37***
Loan Size				976.7	1049.2	-72.49***
Delay (>30 days)				0.0964	0.0765	0.0199***
Default (>180 days)				0.0333	0.0242	0.00904***
Loss				20.10	17.26	2.840

Table D.1 (in Appendix) draws a full comparison based on all characteristics of applications treated by male and female officers. While several differences are significant, female credit officers do not seem to face systematically worse loan portfolios than male. Nonetheless, the female credit officers deal with clients exhibiting *ex post* higher probabilities of delay (9.6% against 7.6% for male officers) and default (3.3% against 2.4% for male officers), but no significant difference in loss.

Chapter 5 exhibits that, under similar conditions, first, female borrowers suffer from loan downsizing and, second, clients served by a female credit officer receive smaller loans. In order to check whether gender matching matters, we now consider the interactions between the client's and officer's gender. For that purpose, we define the couples (i, j) composed of the borrower gender, $i\,(i\epsilon\,\{F, M\})$, and the associated officer gender, $j\,(j\epsilon\,\{F, M\})$. This allows building a variable with four modalities, among which three are included in the regressions, namely (M, M),(F, F), and (F, M). The fourth one ((M, F)), is the omitted reference. Table 6.7 presents the results.

The couples (F, M) and (M, F) reach comparable average loan sizes. Comparing to them, an (M, M) couple brings an extra BRL30 while a (F, F) couple experiences a downsizing of BRL33. The three (i, j) modalities in the regressions exhibit negative coefficients for delay and default probabilities. Consequently, the omitted modality (M, F), is associated to the highest proba-

[9]As depicted in chapter 4, provision-based gender-gap is mainly attributable to credit officers. Indeed, female officers propose smaller loans (BRL 1011) than male (BRL 1076) to the committee that committee adds a marginal contribution to the gender-gap

bilities of delay and default. Nevertheless, regarding the most economically meaningful variable, i.e. the loss, only the couples involving a female clients obtain a significantly negative coefficient.

Table 6.7: Client and credit officer gender combinations

	(1)	(2)	(3)	(4)	(5)
Gender: (Client, Officer)	Approval	LS	Delay	Default	Loss
Male/Male (M,M)	0.00840***	29.40***	-0.0126***	-0.00206*	-3.24
	(0.00253)	(7.380)	(0.00381)	(0.00108)	(2.532)
Female/Female (F,F)	-0.00244	-33.39***	-0.0162***	-0.00334***	-8.706***
	(0.00274)	(7.348)	(0.00351)	(0.000984)	(2.521)
Female/Male (F,M)	0.0109***	1.985	-0.0210***	-0.00455***	-7.568***
	(0.00252)	(7.562)	(0.00396)	(0.00102)	(2.593)
H0: $G_M(X) = G_F(X)$	1.87	0.35	1.98	0.19	1.62
mills or athrho		*	Ns	Ns	Ns
LS	No	No	Yes	Yes	Yes
RA & Other cont	Yes	Yes	Yes	Yes	Yes
Observations	33530	33530	33530	33530	33530

Heckman's selection: committee approval, marginal effect at the mean in (1), (3) & (4).
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

To what extent are these results linked to gender matching? In order to examine that issue from the credit officer perspective, we define $LS(i,j)$ the loan size for couple (i,j) and $G_j(LS) = LS(M,j) - LS(F,j)$ the gender-gap between male and female borrowers only when attended by officer of gender j. Then, $G_F(LS)$, respectively $G_M(LS)$, is the difference in loan size between male and female borrowers existing in female, respectively male, officers' portfolios, all other things being equal. We define more generally the gender-gap in any variable X by $G_F(X)$ in female and $G_M(X)$ in male officer portfolio.

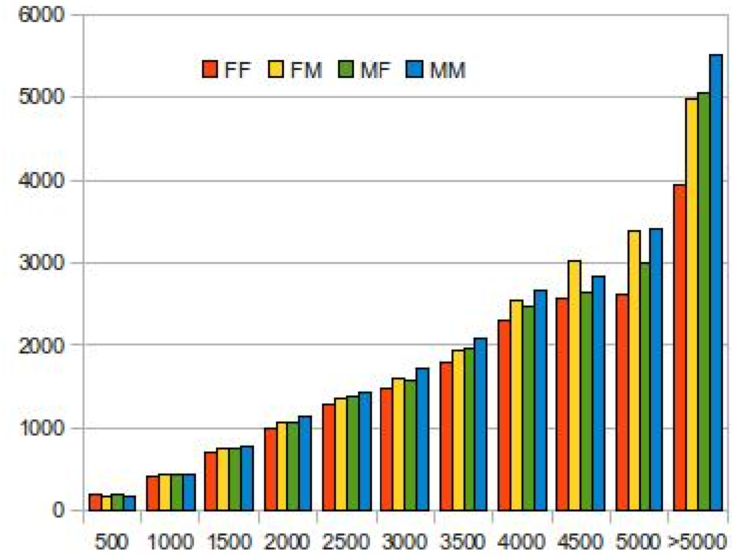
In table 6.7, we perform a t-test comparing gender-gap between male and female officers' portfolios[10]. According to the test results, gender gaps concerning loan size and repayment quality are similar for male and female officers. Neither the loan downsizing suffered by female borrowers neither their better repayment behavior are linked to the gender of the attending credit officer.

Still, male and female officers exhibit different screening behaviors. Why? Table 6.6 provides some clues since it shows that female officers tend to attribute smaller loans. As female applicants are known to ask for smaller loans, we investigate whether there is some matching impact transmitted through the level of requested amount.

[10]In the regressions, (M,F) is the reference modality. Therefore, we have by definition the dummy $(M,F) = 0$ and $RA * (M,F) = 0$.

Figure 6.3 represents the average loan size, by requested amount interval, splitting by clients' and borrowers' gender combination ((i,j)). It appears that female officers exhibit no gender gap (difference between the red and green blocks) for small projects (low requested amount) but seem more reluctant than men to offer large loans to women.

Figure 6.3: Average loan size by requested amount interval (by genders)



Requested amount (intervals of BRL500)

The similarity between male and female officers's portfolios, in terms of gender-gap (table 6.7), has to be mitigated. In order to take in account the scale of the project, to compare male and female officers, three interaction terms between requested amount and the (i,j)'s couples are added to the previous model specification. We end up with six coefficients of interest regarding the matching issue. Table 6.8 presents the estimation result and is completed by two graphics. Figure 6.4, respectively 6.5, represent the loan size, resp. the loss, depending on the requested amount for each couple (i,j)[11].

Consider for instance the couple (F,F) formed by a female client and officer. The corresponding red long dashed line for loan size is obtained as follows. First, its ordinate at the origin is equal to 124.5 that is the coefficient of the dummy (F,F) in the loan size equation (2), see table 6.8 (upper block). Second, the slope is equal to -0.126, that is the coefficient of dummy $RA{*}(F,F)$ in equation (2), see table 6.8 (lower block).

[11]In theory, we should thus have four lines on each picture, but some couples display identical graphs. We end up with three different line for loan size, and two different lines for loss.

Table 6.8: Approval and repayment by gender combinations

	(1)	(2)	(3)	(4)	(5)
Genders: (Client,Officer)	Approval	LS	Delay	Default	Loss
Male/Male (M,M)	0.00820**	-51.44***	-0.00914	-0.00243	0.194
	(0.00375)	(10.56)	(0.00561)	(0.00159)	(3.693)
Female/Female (F,F)	0.00451	124.5***	-0.0188***	1.87e-06	-2.637
	(0.00391)	(11.10)	(0.00555)	(0.00178)	(3.888)
Female/Male (F,M)	0.0173***	16.47	-0.0233***	-0.00531***	-9.583**
	(0.00344)	(11.07)	(0.00576)	(0.00146)	(3.868)
Requested Amount (RA)	-8.08e-06***	0.622***	2.18e-05***	5.03e-06***	0.00768***
	(1.82e-05)	(0.00440)	(3.16e-06)	(9.63e-07)	(0.00196)
RA*(M,M)	3.40e-07	0.0553***	-2.16e-06	4.81e-07	-0.00221
	(1.45e-06)	(0.00512)	(2.76e-06)	(1.02e-06)	(0.00179)
RA*(F,F)	-4.61e-06**	-0.126***	2.06e-06	-3.31e-06***	-0.00463**
	(2.07e-06)	(0.00627)	(3.22e-06)	(1.23e-06)	(0.00220)
RA*(F,M)	-5.31e-06**	-0.00824	2.02e-06	1.05e-06	0.00197
	(2.17e-06)	(0.00592)	(3.15e-06)	(1.11e-06)	(0.00207)
mills or athrho		Ns	Ns	Ns	Ns
LS	No	No	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Observations	33530	33530	33530	33530	33530

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Heckman's selection: committee approval, marginal effect at mean reported in (1), (3) & (4).

The results in table 6.8 and figures 6.4 and 6.5 contrast with the ones in table 6.7. Actually, gender matching matters when interacting with the scale of the project. For example, a woman with a BRL300 project receives an average extra loan size of BRL88 if she deals with a female credit officer rather than a male officer (or (M, F)). In turn, a man having the same project scale dealing with male credit officer receive BRL35 less than with a female officer (or (F, M)). Small project holders, among which a majority of women, are thus favored by the female credit officers. As the smallest projects typically emanate from the poorest applicants, we interpret the results as an evidence that female officers are more socially oriented.

On the opposite, female officers are less prone than their male colleagues to offer large loans to female applicants. The (M, M) slope in figure 6.4 (blue short dashed line) exhibits the sharpest increase of loan size with respect to requested amount, while the (F, F) line (long dashed red) has the lowest slope. On about the average loan size, the (M, M) and (F, F) lines intersect. Thus, when the requested amount is higher than BRL 1000, male clients served by male officers get larger loans than female clients served by female officers. The mixed cases ((M, F) and (F, M)) are equivalent (yellow line) and range in-between the same-sex cases.

Figure 6.4: Predicted loan size(BRL)

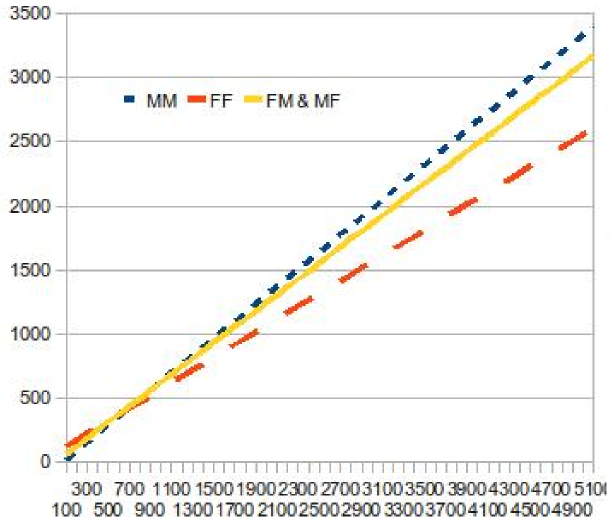
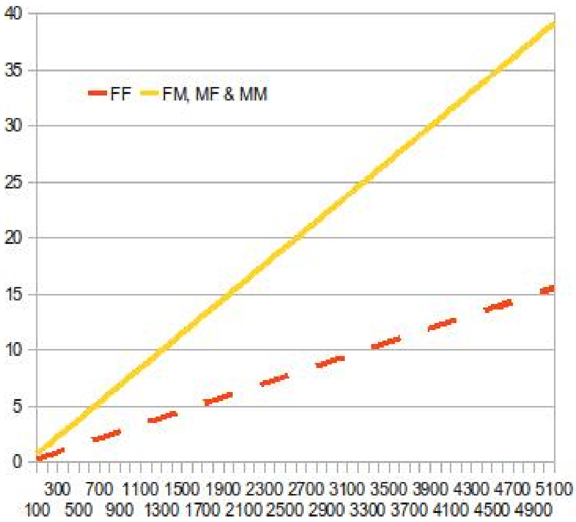


Figure 6.5: Predicted Loss (BRL)



Requested amount (in BRL)

Summing up, on the one hand, any applicant introducing a loan request for a modest project is better-off when treated by a female officer. This is even more true for female applicants. On the other hand, bigger project are always more appreciated by male credit officers, especially when the applicant is male.

Higher delay and default probability might be seen as the price female officers pay for being more generous toward the poorest applicants[12]. Nevertheless, repayment problems are less pronounced for female clients served by female credit officers (see the red long dashed line in the loss graph on fig.6.5). The harsher credit rationing suffered by those female clients is not economically justified. Indeed, the comparison of figure 6.4 and 6.5 makes it clear that the differential treatment in loan size inflicted to women is not driven by higher implied losses. Moreover, the superior repayment conduct of female borrowers observed in chapter 5 is attributable to the harsher attribution condition made by the female credit officers. This results can be related to a difference of risk aversion between both client's and officer's gender.

6.5 Conclusion

The theoretical model in section 6.2 has shown that taste-discrimination in lending implies that the most able individuals from the prejudiced group end up being the most credit constrained, through either loan denial or loan

[12]Credit officers receive a bonus additionally to their basic wage. This bonus depends positively on the number of clients attended and negatively on the average delay above 30 days and on the default and loss of their portfolio.

size reduction. The empirical evidence based on disaggregated data from a Vivacred exhibits mixed results regarding the presence of discrimination. As loan approval rate seems fairly distributed across gender, the loan size is clearly biased in favor of male clients. Moreover, the theoretical prediction that more able women receive proportionally smaller loans is confirmed through quadratic regressions ("concavity effect"). This gendered loan-size effect is robust to several econometric specification.

On the empirical side, this chapter raises serious doubts about two assumptions commonly made in empirical microfinance papers. First, the gender dummy is not an appropriate poverty proxy for at least two reasons: 1) it mixes poverty and potential discrimination, and 2) women tend to ask for smaller loans than men with similar characteristics. Second, an MFI's average loan size is an unsatisfactory measure of mission fulfillment. On top of being abusively penalizing for cross-subsidization (Armendariz & Szafarz (2009)), average loan size may be artificially reduced by unfair credit rationing of some clientèle segments. Therefore, we favor the use of outreach, preferably weighted by some indicator of clients' level of poverty.

At the first glance, credit officer's gender does not matter for gender-gap in loan size. Male credit officers tend to offer larger loans than female ones, but female applicants are treated in an equally unfair way by male and female officers. Therefore, our findings do not support the "gender affinity" hypothesis in the spirit of the "cultural affinity" theory tested for in mortgage lending (Hunter & Walker (1996); Bostic (2003)).

We found a compensation from female credit officer to female client only for small loans. Considering bigger loans, female clients downscaling is stronger when attended by female than by male officer. In a certain way, female officer are strengthening the glass ceiling. As the officer's gender is not taken into account in our model, this result does not invalidate the previous findings.

Borghans et al. (2009) provide an interesting explanation in a survey on financial psychology literature. Woman are more risk adverse both in their personal and professional life which includes business activities and decision making by a bank manager. Smaller requested amount from female client and glass ceiling strengthening by female officers are coherent findings with Borghans et al. (2009). Risk aversion combination from female client and credit officer seems to be an issue and lead us to consider Carter et al. (2007) contribution. Based on data from a main U.K. clearing bank, they found an important difference between male and female officers to negotiate loan applications but little in the assessment criteria used.

The scope of this chapter goes beyond microcredit and gender issues. Actually, the theoretical model is applicable to any kind of potential discrimination in lending. The current literature is mostly focused on denial (or approval) rate. Our results show that examining loan size may reveal insightful as well. Getting a required loan is good news for an entrepreneur, but when it comes to investing it for business purposes the loan size matters more.