5 The Curse of the Trustworthier Sex: Is the Gender-Gap Economically Justified?

with Ariane Szafarz

5.1 Introduction

Microfinance has shed light on the poverty status of women in developing countries. Meanwhile, the sector's experience has also shown that women are trustworthier than men in terms of repayment conduct (de Aghion & Morduch (2000)). Despite this experience, women keep being more credit rationed than men by Microfinance Institutions (MFIs) (Buvinic & Berger (1990); Fletschner (2009); Agier & Szafarz (2010)), a puzzling evidence that poverty alone fails to explain. Built on the unique database from Vivacred, this chapter scrutinizes the economic justification of gender discrimination depicted in chapter 4. It examines the consistency of the loan allocation outcomes with the observed delay, default, and loss in repayment.

Evidence pertaining to access to credit in developing countries is mostly based on household surveys. This approach provides valuable information on the demand side of the market but is unable to reflect the supply-side perspective. In their literature review, Morrison et al. (2007) state that: "*The existing research on credit markets in developing countries - admittedly scarce - suggests that by and large women receive unfavorable treatment not because of discriminatory treatment per se, but rather because of gender differences in individual characteristics that are relevant for loan qualification*" (p. 39). Because the body of evidence is demand-sided, we argue that such conclusion is premature. Indeed, as emphasized by Diagne et al. (2000) credit limits typically emanate from the lenders. Unfortunately, due to data unavailability, the way MFIs assess creditworthiness and grant loans has hardly been investigated yet, let alone the gender issue[1]. Benefiting from exhaustive information gathered by an MFI on its loan applicants and borrowers over an eleven-year period,

[1]Exceptions include Buvinic & Berger (1990) who obtained data from the Urban Small Enterprise Development Fund in Peru, and Marrez & Schmit (2009) who analyze the credit risk of a leading Maghrebian MFI.

our contribution aims at filling this gap.

Women empowerment is a remarkable achievement of microfinance. By providing financial access to poor female entrepreneurs, MFIs undoubtedly play a crucial role in developing countries. Microfinance increases the women's bargaining power and social capital (Hashemi et al. (1996); Pitt et al. (2006). Nevertheless, being highly subsidized, the sector is questioned on its efficiency regarding the promotion of female economic activity. Authors have shown that female access to credit may be accompanied by financial vulnerability (Goetz & Gupta (1996); Garikipati (2008); Guérin et al. (2009)), especially within male-chauvinist societies. In that line, gender-sensitive policies are advocated (Kabeer (2001); Hunt & Kasynathan (2001); Corsi et al. (2006)). Identifying discriminatory practices, if any, and taking steps to eradicate them are key in that respect.

Discrimination in the lending industry has been detected in various countries, notably in the US where it is a legal offense[2]. The literature[3] has thoroughly discussed the pros and cons of various econometric tools designed for assessing the presence of disparate treatment. No consensus has emerged so far (Dymski (2006)). While limitations in that field are mainly data driven, two broad complementary approaches coexist (Blanchard et al. (2008)). First, fair access to credit is tested on denial rates and credit conditions. Second, given that the lender's profit is driven by repayments, gender- and/or race-specific creditworthiness is assessed through default rates and implied losses (the latter being the sounder in economic terms). In order to reach robust conclusions, this paper combines the two approaches[4].

The first part of this chapter is methodological. It summarizes the state of the art on assessing discrimination in lending, with a special focus on gender. In many parts of the world, including developing countries, the

[2]The US legal framework against discrimination in lending includes the 1968 Fair housing Act, the 1974 Equal Credit Opportunity Act, and the 1975 Home Mortgage Disclosure Act. Since 1989, the lenders must report the race and ethnicity of their loan applicants. Besides, the evidences of discrimination in lending observed in other countries are surveyed in Agier & Szafarz (2010)

[3]Race and gender discrimination has been scrutinized by, e.g., Munnell et al. (1996); Schafer & Ladd (1982); Cavalluzzo & Cavalluzzo (1998); Turner & Skidmore (1999); Ross & Yinger (2002); Blanchflower et al. (2003); Han (2004); Cavalluzzo & Wolken (2005); Blanchard et al. (2008)

[4]In that way, we follow Ross & Yinger (2002) recommendation; "(...) *well known methodological problems, such as selection and endogeneity bias, could lead to disparate-impact discrimination even when the designers (...) are trying hard to avoid it. Scholarly access to loan performance data and careful research are needed to shed further light on these issues*" (p. 298).

borrowers characteristics are scarcely disclosed, which in turn restricts the testing opportunities. In that respect, the provision of detailed individual data, like those used in this thesis, allows for a deeper investigation of the screening process.

Our second contribution is empirical. The database includes not only the personal characteristics of all loan applicants, but also those of all credit officers making propositions to the credit committee. We are thus able to trace any loan application that entered the MFI, and deliver an econometric analysis that goes beyond the existing literature. In the regressions, we use all screening variables used by the MFI, which turn our results less subject to missing variable problem[5] that often plagues studies on discrimination (Ross & Yinger (2002)).

All other things being equal, the impact of being a female borrower, rather than a male, is significantly negative on credit conditions[6], but positive on creditworthiness. The gender discrimination is not justified by the repayment behavior. In a second step, we make gender interact with credit history, and show that the information asymmetry reduction brings no remedy to the handicap of being female. Bigotry thus appears the most likely cause for discrimination.

This conclusion is reinforced by taking into account the gender of the guarantors (spouse and/or external guarantor), if any. A male guarantor generates excess credit from the lender, while a female guarantor has no significant impact. This result provides a hint on the discriminatory mechanism at stake: whatever their actual creditworthiness, women lack credibility in the credit officer's eyes.

The rest of this chapter is organized as follows. Section 5.2 describes our dataset and methodology. Section 5.3 provides evidence of gender discrimination that is neither economically justified, nor tempered by existing relationship with the lender. Section 5.4 concentrates on the differentiated gender impact of the credit guarantors. Section 5.6 concludes.

[5]Admittedly, our results may be suffering from the self-selection bias put forward by Cavalluzzo (2002).

[6]In the NGO under scrutiny, credit terms boil down to loan size only as the social-oriented lending policy imposes a flat interest rate.

5.2 Data and Methodology

5.2.1 Descriptive Statistics

Vivacred's lending technology is based on credit rationing, with a flat monthly interest rate of 3.9%[7]. Any loan applicant needs to enter a detailed file, and be interviewed by a credit officer. Credit is accessible to at-least-six-month old businesses. The application file includes the applicant's personal situation, household's budget and firm's financial statements. The spouse of a married applicant has to sign the contract as well. Whether married or single, the majority of applicants also provide an external guarantor.

Client personal profile and relationship with Vivacred, credit and business characteristics, have already been described in the previous section. Table 5.1 depicts, for provided loans, descriptive statistics on requested, proposed and provided amounts as well as delay and default probabilities and loss amount for all loans and separating by gender. A Student t-test for equal mean between genders is performed for each variable.

Table 5.1: Global and gender-specific descriptive statistics

	Global Mean	**Std. Dev.**	**Mean Male**	**Mean Female**	**t-test**[a]
Female client (share)	0.496	0.500			
Female credit officer (share)	0.4741	0.4993	0.459	0.490	-0.0311***
Request, loan size, and repayment record					
Requested Amount (All,BRL)	1388	1240	1524	1250	274.0***
Requested Amount (BRL)	1380	1242	1518	1237	280.7***
Loan size (in BRL)	1015.47	996.63	1136.5	891.1	245.3***
Delay (30 days)	0.086	0.281	0.094	0.078	0.0165***
Default (180 days)	0.029	0.167	0.030	0.027	0.003
Loss (in BRL)	18.59	156.04	21.36	15.47	5.888***
Ratio: loss over loan size	2.521	15.286	2.753	2.287	0.465**
Observations	31,670		15,962	15,708	

[a]t-test for equal mean between genders; *** p<0.01, ** p<0.05
[b]All the financial values are in BRL per month. BRL denotes the Brazilian currency (Real). Over the period under consideration, the BRL fluctuated between 0.270 and 0.588 USD

Female clients request smaller loans than men[8] (BRL 1237 against BRL 1518), and logically receive smaller amounts (BRL 822 against BRL 1035).

[7] *Banco da Mulher*, a comparable non-profit institution, provides loans with rates between 3% and 5% a month, while *Fininvest*, a for-profit institution, proposes consumption credit with a monthly 12% rate.

[8] The data in Table 5.1 concern granted loans only. The mean requested amount for all applicants, including the denied ones, is BRL 1250 for women and BRL 1524 for men.

However, women are more credit rationed than men as they get, on average, 78% of their requested amount,while the mean ratio is 79.3% for men.

Female borrowers exhibit a lower probability of delay than male ones (7.8% against 9.4%), but a similar probability of default (2.9%). The overall default rate (loss over outstanding loan) of Vivacred is 2.5% (2.7% for male clients, 2.3% for female clients) conform to the typically low default rates observed in the microfinance sector[9].

Most importantly, women exhibit significantly smaller losses for the MFI, even when divided by loan size. The mean loss is equal to 2.3% of the loan outstanding for a female borrower, and 2.8% for a male borrower. The descriptive statistics are thus is line with the stylized facts that women receive smaller loans and reimburse better than men. Section 5.3 will examine whether this conclusion derived from rough mean values resists the multivariate analysis.

5.2.2 Methodology

Previous chapter has uncovered that female applicants receive a differentiated treatment regarding credit conditions (in loan size but not in denial). The present chapter aims at testing whether this difference if economically justified.

While definitions slightly vary across papers, gender[10] discrimination in lending is generally split into two broad categories. On the one hand, *taste-based discrimination* (Becker (1971)) originates from stereotypes and bigotry, shown by social psychologists (Fein & Spencer (1997); Kunda & Sinclair (1999) to be common human features. On the other hand, *statistical discrimination* (Arrow (1971, 1998)) is economically justified. In this case, because some variables affecting creditworthiness are not observable (e.g., business abilities, social connections, etc.), lenders might adopt gender as a proxy for credit risk[11].

[9]The default rate of CrediAmigo in Northeast Brazil never exceeded 2.2%. Morduch (1999) reports defaults rate below 5% for Grameen in Bangladesh. Robinson (2002) report between 1% and 5.5% (except one at 12%) for rural MFI's in Indonesia.

[10]The focus of this paper is on gender, but similar definitions apply to race, ethnicity, disability, etc.

[11]Some empirical papers in microfinance use the gender dummy as a proxy for poverty. If results drawn from those papers where applied to actual loan granting, they would induce statistical discrimination.

Because data are generally insufficient to trustfully reproduce the lender's creditworthiness assessment, taste-based and statistical discriminations are often hard to disentangle in practice. Thanks to Vivacred remarkable database, this chapter offers a way to circumvent this identification problem. Still, econometric testing for discrimination raises challenging issues.

First, discrimination may arise in the loan allocation (higher denial probability) and/or in loan conditions (higher interest, smaller loans, more collateral). However, selection screening and loan terms do not concern the same pool of applicants as credit conditions are observed only for those who successfully passed the selection. Heckman (1976, 1979) methodology is widely used to address this selection issue in a proper way.

Second, the impossibility to observe the creditworthiness represents the main obstacle in assessing discrimination. It may be dealt with in several ways. Commonly, the surrogate for creditworthiness is composed by a set of relevant variables (ideally, the ones used as screening device by the lender), referred to as "controls", which aim at capturing all non-gender impacts. This approach may suffer from several drawbacks, notably omitted variables.

Additionally, credit risk may be approximated by delay, default, and loss. While this approach is economically sound, it does not solve everything. Indeed, observed defaults are affected not only by the selection bias (default happens only for actual loans), but also by the credit conditions. For instance, default might be more frequent on larger - and presumably riskier - loans (Stiglitz & Weiss (1981)). Alternatively, severely rationed credit could be harder to reimburse[12]. Therefore, endogeneity prevents the default probability from being a straightforward explanatory variable for credit approval and credit conditions. When observable, defaults still offer valuable information provided that endogeneity is properly acknowledged for, merely through a multivariate specification.

Given the lending methodology of Vivacred (single interest rate, no formal collateral), the credit conditions boil down to loan size. Moreover, loan size must be judged according to the amount initially requested by the borrower. Therefore, we consider the requested amount as a relevant factor on top of the personal and business characteristics of the loan applicants. We use the following notations:

[12] The results in section 5.3 show that, in Vivacred, loan size is negatively correlated with delay and default probabilities.

– Gender of applicant[13] for loan i (dummy variable):

$$F_i = \begin{cases} 1 \text{ if applicant for loan } i \text{ is female} \\ 0 \text{ if applicant for loan } i \text{ is male} \end{cases}$$

– Requested amount for loan i (continuous variable): RA_i

– Other characteristics ("controls") associated to loan i (variables of any type): vector $z_{1i}, ..., z_{ni}$

– Approval of loan i (dummy variable):

$$A_i = \begin{cases} 1 \text{ if loan } i \text{ is granted} \\ 0 \text{ if loan } i \text{ is denied} \end{cases}$$

– Size[14] of loan i (continuous variable): LS_i

– Delay[15] on loan i (dummy variable):

$$D_i^{30} = \begin{cases} 1 \text{ if loan } i \text{ is delayed at least once} \\ 0 \text{ if loan } i \text{ is never delayed} \end{cases}$$

– Default[16] on loan i (dummy variable):

$$D_i^{180} = \begin{cases} 1 \text{ if loan } i \text{ is defaulted} \\ 0 \text{ if loan } i \text{ is repaid} \end{cases}$$

– Loss on loan i (continuous variable): $Loss_i$

Given a loan is granted, its size is largely influenced by the lender's default expectations. In turn, observed defaults might depend on loan size as a too small loan (with respect to the project to be financed) is likely to increase the probability of default. Therefore, the *ex post* default rates, used to assess *ex ante* creditworthiness, are to some extent caused by the lender. By essence, "pure" creditworthiness of a prospective borrower is unobservable.

According to Ross (2000) survey, discrimination in lending is tested for either on access to credit, or on credit conditions. Some authors, such as Blanchflower et al. (2003) and Weller (2009), combine the two perspectives.

[13] Actually, each observation corresponds to a loan application, whether successful or not. In that way, a borrower who applies repeatedly appears more than once in the database.
[14] Loan size, default, delay, and loss are defined only for loans such that: $A_i = 1$.
[15] Delay means that the borrower is 30 days delinquent.
[16] Default means that the borrower is 180 days delinquent.

But, whatever their variable of interest, all authors are confronted to some degree of uncertainty concerning the screening process used by the lender.

Identifying discriminatory practices in lending is hard because the univariate analysis of the denial probability (or a credit condition) is confronted to biases due to endogeneity and omitted variables. As put by Dymski (2006), "*One equation models are likely to overestimate the significance of discrimination due to partial observability bias. No single-equation model (...) is adequately identified if the market processes in which it is embedded might differentially affect the comparison groups*"(p. 228).

Ferguson & Peters (1995) argue that disparate denial rates "*certainly attest to economic inequalities in our society, they are not necessarily evidence of discrimination on the part of lenders, and, therefore, should not be a cornerstone upon which policy is formed*" (p. 740). Accordingly, they define discrimination as "*the use of different credit standards across the two components of the population*" and state that discrimination happens when one observes a smaller or equal default rate associated to a higher or equal denial rate, provided that at least one inequality is strict.

Our contribution relies upon Ferguson & Peters (1995) conceptual framework. We apply this framework to loan size (see Han (2004)), and address the selection issue thanks to the Heckman procedure (Heckman (1976, 1979)). Our model simultaneously explains loan attribution, loan size (the only relevant credit condition in Vivacred's methodology), and three repayment-related variables (delay, default, and loss) in the following way:

$$P[A_i = 1] = \sum_{k=1}^{n} \alpha_k z_{ki} + \alpha_F F_i + \epsilon_{1i} \quad (5\text{-}1)$$

$$LS_i = \sum_{k=1}^{n} \beta_k z_{ki} + \beta_F F_i + \epsilon_{2i} \; \forall i \text{ s.t. } A_i = 1 \quad (5\text{-}2)$$

$$P[D_i^{30} = 1/A_i = 1] = \sum_{k=1}^{n} \delta_k z_{ki} + \delta_F F_i + \delta_L LS_i + \epsilon_{3i} \quad (5\text{-}3)$$

$$P[D_i^{180} = 1/A_i = 1] = \sum_{k=1}^{n} \theta_k z_{ki} + \theta_F F_i + \theta_L LS_i + \epsilon_{4i} \quad (5\text{-}4)$$

$$Loss_i = \sum_{k=1}^{n} \varphi_k z_{ki} + \varphi_F F_i + \varphi_L LS_i + \epsilon_{5i} \; \forall i \text{ st} A_i = 1 \quad (5\text{-}5)$$

For sake of simplicity, let us consider the system composed of equations 5-1, 5-2, and 5-3.[17] Following the Ferguson & Peters (1995) rule, unfair denial (i.e. gender discrimination in loan attribution) is suspected if $\alpha_F \leq 0$ and $\delta_F \leq 0$ (higher denial probability but lower delay probability), with at least one strict inequality. Moreover, extended to loan size, the same rule states that unfair loan downsizing (i.e. more stringent credit rationing for women than for men) is suspected if $\beta_F \leq 0$ and $\delta_F \leq 0$ (smaller loan but lower delay probability), with at least one strict inequality.

In our case, the lender is a socially-oriented MFI. What difference does it make when it comes to testing for discrimination? We argue that discrimination in social lending may be addressed in the same way as in profit-based lending. Indeed, for sake of sustainability, socially-oriented lenders are bound to assess their applicants creditworthiness. In practice, MFIs select their clients in two steps. First, according to its social mission, an MFI fixes its lending methodology (for instance, absence of collateral and fixed interest rate) and defines its pool of unbanked prospective borrowers (for instance, the poor in a given area). Second, the MFI examines loan applications from the selected pool only. In this second step, creditworthiness is basically assessed in the same way as in profit-oriented institutions[18]. Therefore, gender discrimination may show off in the same way too, provided that the targeted pool is defined independently from gender considerations, which is indeed the case of the MFI under study.[19]

5.3 Empirical Results

5.3.1 The Gender-Gap is not Economically Justified.

In this section, we compare loan attribution to repayment conduct, and use the Ferguson & Peters (1995) rule to draw conclusions. In section 5.2, we observed that in Vivacred the denial probability is similar for men and women, leading to the conclusion that access to credit is fair. Nonetheless, all things being equal, female borrowers receive significantly smaller loans than men.

[17]The same reasoning applies if equation 5-3 (delay) is replaced by 5-4 (default) or 5-5 (loss). Section 5.3 will consider all three cases.

[18]This way of doing contributes to explaining why MFIs do not reach the very poor (see, e.g., Rhyne (2001))

[19]Such an approach would make no sense for an MFI with specific gender policy. This is, for instance, the case of the Grameen Bank, which explicitly targets poor women.

Here, we check whether harsher female credit rationing is, at least partially, attributable to repayment conduct. We address this issue by estimating equations (5-1) to (5-5)[20]. We control for all variables collected by Vivacred.

The borrower's gender (female dummy F_i) is our explanatory variable of interest. The client's requested amount, RA_i, is a major control variable acting as a proxy for the client's project size. In particular, it allows taking into account that women typically ask for smaller loans. By including this (often unobservable) variable in the regressions we intend to clean the gender dummy variable from demand-sided effect[21].

The other control variables, $z_{1i}, ..., z_{ni}$, are common to equations (5-1) to (5-5). They include the clients characteristics (gender, marital status, dependents, age, and household's extra income), the business characteristics (profits, sector, official status, employees), the loan characteristics (requested amount, guarantor, installments, loan use). The relationship with Vivacred is accounted for by three variables: the number of former loans with Vivacred as a client, as a guarantor, and the number of former loans repaid with delay (as a client). Year and branch dummies are added to capture time and place heterogeneity. The credit officer's gender is included as well.

The first probit regression (equation (5-1)) explains the loan approval probability by the gender dummy, the requested amount and the controls. As unequal selection may create biases, we use Heckman's procedure to estimate equations (5-2) to(5-5). Equation (5-2) explains the loan size. The next three equations pertain to repayment conduct. They concern, respectively, the delay probability (equation (5-3)), the default probability (equation (5-4)), and the loss (equation (5-5)). While the delay and default probabilities are estimated under a Heckman-probit specification, loan size and loss are continuous variables and, therefore, estimated by the classical Heckman method.

[20]Chapter 4 concern is the responsibility share for the gender-gap in loan size. All the applications presented to the credit committee are considered in the regressions. Selection (approval or denial) is a border issue treated by attributing a null value to the loan size in case of denial. In chapter 5, our estimation strategy changes to take in account new concerns. PLS treatment is not needed anymore as we are not interested in the request channel ($c_R a_F$) in gender gap, but only in the provision channel (c_F). Meanwhile, selection treatment become an important issue to examine the repayment behavior. Let's note that the two estimation strategies lead to the same conclusion that women receive significantly less than men for a same requested amount.

[21]Still, we cannot exclude that women try to maximize their chances to get a loan by intentionally introducing small requests. If this is the case, then the request effect is partly supply-driven. More generally, the identification of demand and supply effects in credit markets is discussed by, e.g., Kanoh & Pumpaisanchai (2006); de Janvry et al. (2006).

For each repayment-related variable we consider two possible specifications: with and without loan size among the explanatory variables. Loan size significance would reveal that the endogeneity issue applies to our database. In equation (5-1) and (5-2), the gender dummy should be insignificant for a gender-blind lender.

Table 5.2 presents the regression results for the approval decision, loan size, delay, default, and loss, respectively. The first column (approval decision) is the first equation of Heckman procedure and the remaining columns depict the result of the second equation[22].

Regarding the specification of the repayment-related equations (delay, default, and loss), we face a dilemma. On one hand, including loan size as an explanatory variable in those equations yields an endogeneity problem. On the other hand, excluding loan size drives obvious misspecification, as repayment conduct heavily rests on loan size. To confront this dilemma, we estimated both specifications (with and without loan size on the right-hand term). Although, as expected, loan size reveals significant, its presence does not affect much the other estimated coefficients.

The first two columns of table 5.2 ("approval" and "loan size") confirm the results of chapter 4. Women benefit from fair access to credit but suffer from stronger credit rationing. Moreover, the gender dummy is one of the only two explanatory variables (the other one being the "official business" dummy) that influence the loan size without interfering with credit approval. As the interest rate is fixed and there is no collateral requirement, loan approval and loan size capture all relevant credit conditions.

Even accounting for selection and differential requested amount, female clients receive smaller loans. Those constraints could result from either officer's bigotry, or borrower's gender acting as a proxy for unobservable creditworthiness components (like a lack of access to the household's assets). Equation (5-3) to (5-5) allow for disentangling the two possibilities. Discrimination would (at least partially) be economically justified if women exhibited worse repayment conduct, all other things being equal. Otherwise, discrimination is to be attributed to prejudice.

[22]Controls are the same in the selection equation and in the main equation except for the loan size. Every time there is a change in the equation of interest in the article, the controls in selection equation are adapted.

Table 5.2 shows that, whatever the specification of the repayment-related equations (with and without loan size), female borrowers exhibit significantly better repayment conduct in all three dimensions: less delay, default, and smaller loss. In theory, a harsher credit rationing could create a trade-off in repayment records. First, smaller loans are likely to induce smaller losses. Second, tougher credit constraint can put the underlying project at higher risk, leading to more frequent delay and default, as testified by the negative coefficients associated to loan size, when added in the delay and default specifications.

It is thus remarkable that women actually exhibit significantly less delay and default than men. It means that, despite the handicap of being more credit rationed, female borrowers manage to reimburse their loans in a more timely fashion. In other terms, harsher credit rationing *cannot* be the reason why women exhibit better repayment conduct than men. Therefore, prejudice is the most likely explanation at this stage.

Regarding control variables, a positive influence on both the approval probability and loan size is found for the following explanatory variables: having dependence, being older, using the capital for investment or for repayment, having larger staff, having a relationship with Vivacred. Having experienced past delays and attending a female credit officers[23] have negative impacts on the approval probability and loan size. Applications involving a guarantor are more likely to be approved but, strikingly, do not bring higher loans. It could be due to the fact that a guarantor is not required when the borrower either is known, or asks for a small complementary loan ("credit opportunity").

With few variations, but the notable exception of the borrower's gender, positive impacts on repayment variables are observed from the variables that bring larger loans. For instance, married clients[24] and older clients receive larger loans and repay better. The same is true for borrowers with larger extra income. Loans motivated by capital investment are larger (even when controlling for the requested amount) and are better repaid. Applications from the trade sector (compared to services) are more likely to be approved, but bring smaller loans. Those loans exhibit more frequent default but, given their smaller size, do not generate higher losses.

[23]The behavior of the female credit officers will be further investigated in Section 6.4.
[24]Marriage implies the presence of at least one guarantor (the spouse).

Table 5.2: Probability of approval, loan size, probability of delay and default, and loss

	Approval	Loan	[illegible]	[illegible]	ult (180 days)		Loss	
Female client	1.95e-05	-30.4	[illegible]	[illegible]	***	-0.00327***	-6.380***	-6.396***
	(0.00196)	(5.120)	(0.00261)	(0.00267)	(0.000846)	(0.000857)	(1.751)	(1.752)
Loan size				-2.74e-05***		-7.76e-06***		-0.000549
				(3.04e-06)		(1.22e-06)		(0.00193)
Requested Amount	-9.87e-06***	0.624***	5.33e-06***	2.05e-05***	9.74e-07**	4.66e-06***	0.00607***	0.00642***
	(8.97e-07)	(0.00306)	(1.44e-06)	(2.33e-06)	(4.55e-07)	(7.42e-07)	(0.00104)	(0.00159)
Married client	0.00287	24.99***	-0.0251***	-0.0249***	-0.00527***	-0.00514***	-7.679***	-7.665***
	(0.00203)	(5.319)	(0.00284)	(0.00289)	(0.000926)	(0.000934)	(1.819)	(1.820)
Client with dependent(s)	0.00334	6.613	-0.00160	-0.00150	-0.000321	-0.000331	-3.359*	-3.355*
	(0.00206)	(5.355)	(0.00269)	(0.00276)	(0.000850)	(0.000856)	(1.830)	(1.830)
Client's age	0.000254***	0.473**	-0.000948***	-0.000959***	-0.000172***	-0.000168***	-0.234***	-0.234***
	(8.40e-05)	(0.222)	(0.000121)	(0.000123)	(3.74e-05)	(3.77e-05)	(0.0760)	(0.0760)
Guarantor involved	0.0698***	-18.31	-0.00457	-0.00475	-0.00254	-0.00248	-0.626	-0.634
	(0.00695)	(12.94)	(0.00681)	(0.00688)	(0.00211)	(0.00215)	(4.422)	(4.423)
# of installments	-0.00146***	24.40***	0.00169***	0.00246***	0.000396***	0.000562***	1.287***	1.300***
	(0.000221)	(0.660)	(0.000328)	(0.000351)	(9.87e-05)	(0.000107)	(0.225)	(0.229)
Capital investment	0.0142***	28.96***	-0.00723**	-0.00664**	-0.00207**	-0.00181**	-5.091**	-5.074**
	(0.00200)	(6.185)	(0.00291)	(0.00296)	(0.000892)	(0.000909)	(2.111)	(2.112)
Loan repayment	0.0232***	96.26***	0.0742***	0.0797***	0.0186***	0.0207***	24.68***	24.74***
	(0.00229)	(10.19)	(0.00783)	(0.00811)	(0.00300)	(0.00321)	(3.472)	(3.477)
External income	1.98e-05***	0.0794***	-9.35e-06***	-8.14e-06**	-5.60e-06***	-4.94e-06***	-0.00308	-0.00304
	(2.97e-06)	(0.00754)	(3.59e-06)	(3.67e-06)	(1.58e-06)	(1.61e-06)	(0.00257)	(0.00258)
Business profit	5.54e-06***	0.0561***	1.57e-07	1.46e-06	2.81e-07	5.38e-07	0.00274***	0.00277***
	(5.49e-07)	(0.00262)	(1.05e-06)	(1.12e-06)	(2.89e-07)	(3.43e-07)	(0.000892)	(0.000899)
Trade (sector)	0.0101***	-21.54***	-0.000222	-0.000963	0.00191**	0.00175**	0.889	0.878
	(0.00205)	(5.515)	(0.00270)	(0.00277)	(0.000849)	(0.000855)	(1.881)	(1.881)
Official business	-0.00137	180.2***	0.00762	0.0153**	-0.000432	0.00156	0.822	0.921
	(0.00470)	(11.77)	(0.00588)	(0.00656)	(0.00204)	(0.00244)	(4.027)	(4.042)
# of employees	0.00244***	9.425***	0.000553	0.000841*	-2.45e-05	9.40e-05	0.431	0.436
	(0.000652)	(1.217)	(0.000513)	(0.000505)	(0.000285)	(0.000265)	(0.416)	(0.416)
# of former loans at Vivacred	0.00540***	31.69***	-0.0127***	-0.0112***	-0.00307***	-0.00265***	-1.717***	-1.700***
	(0.000446)	(1.048)	(0.000928)	(0.000903)	(0.000286)	(0.000281)	(0.358)	(0.363)
# of times acted as a guarantor	-0.00027	8.519***	-0.00594***	-0.00553***	-0.00140***	-0.00129***	-1.266***	-1.261***
	(0.000537)	(1.258)	(0.00109)	(0.00111)	(0.000345)	(0.000344)	(0.430)	(0.430)
# of past delays	-0.0343***	-120.3***	0.0906***	0.0879***	0.0188***	0.0179***	39.15***	39.08***
	(0.00435)	(14.33)	(0.00726)	(0.00713)	(0.00189)	(0.00192)	(4.884)	(4.890)
Female credit officer	-0.0114***	-32.19***	0.0102***	0.00929***	0.00205**	0.00182**	1.077	1.059
	(0.00207)	(5.558)	(0.00288)	(0.00293)	(0.000858)	(0.000864)	(1.900)	(1.901)
Constant		-203.6***					-0.153	-0.246
		(29.32)					(6.897)	(6.905)
mills or athrho		**	Ns	Ns	Ns	Ns	Ns	Ns
Years' & branches' dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33530	33530	33530	33530	33530	33530	33530	33530

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1, Ns: non significant. Marginal effects at the mean reported for the probit regressions.
The loan size, delay, default, and loss equations are estimated with the Heckman procedure (selection: loans approved by the credit committee).

More installments reduce the approval probability. Mechanically, the loan size increases with the number of installments. For given loan size and requested amount, the higher the number of installments, the worse the repayment conduct. More profitable businesses receive larger loans but, surprisingly, register more losses. As expected, all client history indicators are significant in all equations: more former loans (as a borrower and/or a guarantor) leads to larger and better repaid credit. Former delays act in the opposite way.

The credit officer's gender is significant for loan allocation. Female officers are more reluctant to offer loans and, when they do, opt for smaller amounts that are repaid with more frequent delay and default, but without any significant extra loss. Next chapter (in section 6.4), further analyzes the impact of the officer's gender.

Summing up, women get smaller loans but repay swiftly than men and generate less losses, even when taking into account the harsher credit rationing they suffer from. Our results thus provide a significant evidence of taste-based discrimination against female borrowers.

5.3.2 Relationship does not Smooth the Gender-Gap.

We now address the dynamics of gender-specific treatment along the borrower's credit history, and test for the resilience of the already detected discriminatory practice.

Relationship reduces information asymmetry. Indeed, timely repayments demonstrate the client's creditworthiness. Therefore, after a first loan is successfully reimbursed, the client more easily obtains a second loan, which is, on average, larger than the first one, and so on. This is the basic principle driving progressive lending (Egli (2004)). For instance, Chakravarty & Scott (1999) show that relationship duration lowers the probability of being credit rationed in consumer loans. Our previous estimations (table 5.2), confirm that the number of previous loans has a positive impact on both the approval probability and loan size.

The positive impact of relationship is economically sound. However, if irrational bigotry is strong enough, relationship could reveal insufficient to change the credit conditions. In this case, repayment history might not matter.

In such a case, the agent is going to stick to the same level of unfair loan downsizing.

Alternatively, although being originally biased against females (for instance, for cultural reasons), some credit officers could learn from experience about their female clients. In that case, one should observe some discrimination mitigation arising with the number of previous loans. Relationship would then exhibit a stronger (positive) impact for female borrowers than for male, allowing the former to be treated in a progressively fairer way with time, because the credit officers learn about their true personal creditworthiness.

In order to disentangle the two possible scenarios, we now plug in a gender-specific "relationship" factor into our model by means of an interaction term. Namely, we introduce an additional explanatory variable expressing the product of the number of former loans and the gender dummy. The sign of the associated coefficient, if significant, indicates whether the impact of relationship differs across genders.

Our database includes 11,422 borrowers, among which 63.31% benefited from a second loan. About one-third of the first-time borrowers never came back. For them, we ignore what would happened for subsequent loans. We thus face here a second selection issue, leading again to using the Heckman estimation procedure. [25]

Table 5.3: Gender gap along the credit history

	(1)	(2)	(3)	(4)
Heckman's 2^{nd} equation	LS	Delay	Default	Loss
Female client (F)	-14.69*	-0.0124***	-0.00337**	-2.699
	(7.605)	(0.00332)	(0.00159)	(2.053)
# of former loans	33.95***	-0.00503***	-0.00140***	-0.741**
	(1.227)	(0.000856)	(0.000476)	(0.335)
# of former loans * F	-8.118***	0.00172*	0.0006	-0.176
	(1.771)	(0.00102)	(0.000411)	(0.479)
mills or athrho	**	Ns	Ns	*
Loan size	No	Yes	Yes	Yes
RA & Other controls	Yes	Yes	Yes	Yes
Observations	33530	33530	33530	33530

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Heckman selection: got at least a second loan, marginal effect for (2) and (3).

[25] As the Heckman procedure allows for one selection only, we applied it in two different ways. First, we considered the pool of all applicants. Second, we restricted the analysis to the pool of applicants who benefited from a previous loan. In both cases, the selected clients are the ones who obtain a second loan. As both exercises brought similar figures, we only present the estimations pertaining to the pool of all applicants. It has the merit of being consistent with the previous regressions.

Table 5.3 confirms that relationship makes loan size increase and repayment conduct improve. Delay and default probabilities decrease, and loss is reduced, in a gender-insensitive way. However, table 5.3 also shows that the interaction term has a significantly negative effect on loan size. While men benefit, on average, of an extra BRL 33.95 for each successful former loan, women see this bonus reduced by BRL 8.118, thus amounting BRL 25.83 only, per former loan.[26] Credit restrictions are progressively relaxed, but more slowly for women. Relationship, while positive for all borrowers, is less valued for females, digging the gender-gap instead of reducing it.

In conclusion, discrimination is getting worse along the credit renewals. Starting with smaller first loans, women never recover from their initial handicap. On the contrary, the gender gap in loan size widens with successful credit history. This result adds to advocating in favor of the presence of taste-discrimination, rather than statistical discrimination.

5.4 What is a woman's involvement worth?

Building on the finding that female borrowers are not seen by the MFI as trustworthy as they actually are, we enlarge the scope to all women involved in a given credit. In Vivacred, each contract involves at most three persons from the borrowing side: the client, the client's spouse, and the guarantor. Each of them is at risk in case of default. Indeed, they all bear the risk of being having their name written down in the SPC register (Brazilian register of bad payers) and, consequently, experiencing serious trouble in future financial transactions[27].

From the lender viewpoint, having more people involved in a credit contract is always better[28]. This explains why married borrowers and borrowers

[26]Loan size and credit records are also increasing with relationship as a guarantor, but at a slower rate. A former loan as a client brings a gain in loan size four time larger than as a guarantor. Nonetheless, the impact of history as a guarantor is gender-insensitive. Moreover, former loans with delay have a negative impact on loan size and, consistently, on repayment. The "stick effect" is stronger than the "carrot effect" as a former loan with delay brings a loss in loan size six time larger than the gain from a former loan without delay.

[27]All guarantors have to provide their fiscal identity number (CPF), which is the necessary code for registering them within the SPC. Some borrowers spouse succeed in escaping from this identification. In order to check whether this change matters, we added to the specification a dummy variable associated to married borrowers without an identified spouse. As the coefficients associated to this dummy variable revealed insignificant in all regressions, and did not affect the other coefficients, we abandoned it.

[28]Though, Alesina et al. (2008) mention that the presence of a guarantor might signal a borrower's higher credit risk

accompanied by an external guarantor benefit from larger loans. However, until now, we have investigated the gender issue for the borrower only. Here, we extend the analysis by taking into account the gender of all involved partners, referred to as "the borrowing team".

A borrowing team is composed of one-to-three persons.[29] Genders are well-balanced among the clients, 49.6% being female. The proportion of married clients is 48%. However, male borrowers are more frequently married than female ones (52.5% against 42.6%). When a guarantor is involved (93%), this person is a male in 57.4% of the cases, with no significant difference between male and female clients.

Table 5.4 summarizes the composition of the borrowing team. As same-sex couples are not considered, no team includes three men or three women. Given that most loans involve guarantors, and male guarantors are more frequent, the most prevalent team is composed of two men and one woman (26.81%). It is followed by the two-women-and-one-man situation (18.94%). Among the two-partner teams, the one-man-one-woman case (23.41%) is the most frequent one, followed by the two-men (13.46%), and two-women (12.29%). Single-person teams are rare (one woman: 2.97%, one man: 2.11%).

Table 5.4: The "borrowing team" composition

	No woman	One woman	Two women	Total
No man	0	2.97	12.29	15.26
One man	2.11	23.41	18.94	44.47
Two men	13.46	26.81	0	40.27
Total	15.57	53.20	31.23	100.00

In section 5.3.1, we have controlled for the team size as the regressions included dummy variables for married clients and for guarantor's involvement. Implicitly, we also controlled for the spouse gender as the client's gender is specified. Here, we study the impact of gender irrespectively of the person's status in the borrowing team. To do so, we take out the three dummies: "client's gender", "married client", "guarantor" and introduce two new explanatory variables: "number of females in the borrowing team" and "number of males in the borrowing team".

[29]In table 5.4 and 5.5, we neglect the cases of multiple guarantors and consider only the gender of the main guarantor (with the higher income). The same exercise with the complete team (with the exact number of male and female guarantors) is provided in appendix in table C.1. Conclusions are similar.

We then re-estimate the full system. In that way, we measure the additional loan size brought by either a female team member, or a male team member. Given that teams made up of more persons are more attractive to the lender, we expect the two new variables to exhibit positive coefficients in both the approval probability and loan size equations.

The first column of table 5.5 proves that this is indeed the case for the approval rate. Still, the Student-test statistic for equal coefficients shows that the extra approval probability brought by a male team member is larger than the one brought by a female member (at the 5% level of confidence). Further, the second column of table 5.5 reveals that an additional woman in the borrowing team brings no significant extra loan size. On the opposite, each male team member brings a significant premium of BRL 21.44 in loan size.

Table 5.5: Gender gap in the "borrowing team"

	(1) Approval	(2) LS	(3) Delay	(4) Default	(5) Loss
Number of females	0.0143***	1.437	-0.0269***	-0.00538***	-7.340***
	(0.00196)	(5.585)	(0.00445)	(0.000923)	(1.882)
Number of males	0.0158***	21.44***	-0.0227***	-0.00360***	-3.893**
	(0.00185)	(5.616)	(0.00432)	(0.000848)	(1.889)
Test (coefficient equality): Number of Female = Number of Male					
$\chi^2(1)$	4.59**	22.30***	3.63*	6.13**	5.86**
mills or athrho		***	Ns	Ns	Ns
LS	No	No	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Observations	33530	33530	33530	33530	33530

Heckman's selection: committee approval, marginal effect for col. (1), (3) and (4).
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The coefficients in equations (3) to (5) in table 5.5 confirm that any additional team member significance improves repayment conduct (controlling for loan size). Moreover, the coefficient associated to female team members is significantly larger, in absolute value, in the three regressions (but only at the 10% level of confidence for the delay reduction). In other words, despite being ignored in loan size determination an additional woman in the borrowing team is more profitable to the lender than an additional man.

Women involved are not taken seriously by the credit officers although they lead to better repayment outcomes than men. We interpret this gender gap in the borrowing team as a lack of credibility. Women social capital is possibly caused by stereotyping. Alesina et al. (2008) reach similar conclusions from a study on the overdraft contracts between banks and small businesses in Italy[30].

Moreover, the fact that male guarantors are more frequent than female ones can be viewed as a testimony that some borrowers are aware of this phenomenon. Of course, most borrowers, especially among the poor, do not have many options when it comes to finding a guarantor.

5.5 Gender-gap nature: Occupationnal choice

The gender-gap in loan size could be linked with the occupationnal choice than can be different in terms of profitability, collateral (equipmement), or even activity nature some requiring phisical ability. For exemple, a taxi could be easier to seize than an hairdresser equipement, the first one being an activity hold more frequantly by men while the second one by women.

Until now, we have used a restricted information about the sector of activity: service, trade or other sector. The database, offers a more detailed information about activities. However, this information is collected for field purpose and would need to be organized in an adequate classification designed for research purpose. In this section, the classification is not complete and pretend only give an insight of detailed activity contribution. A twelve categories classification was created based of more than 300 activities. The last one, "other" is heterogeneous and would need to be more deepely explored.

Table 5.6 present descriptive statistics and regression results taking in account this activity classification. Each line represent a subsample. The First four columns presents descriptives statistics for each subsample: the number of observations, the proportion of women, the average loan size and requested amount. The last two columns present the female dummy coefficient from the loan size and the loss regression for each subsample. The first line recalls results found in the general sample and the seond one depicts loan size and loss regression results obtained including activity dummies in the controls. Then, activities (in line) are ranked by scale (average loan size or request).

The overall sample results confirm the previous ones, gender-gap, even very small, is still significant even contoling for detailed activity. Female coefficient are slitly smaller in this case in the two regressions. However,

[30]Actually, Alesina et al. (2008) study the cost of credit. They find that " *when a female borrower has a male guarantor, she pays substantially less, but when a female borrower has a female guarantor, she pays a lot more!*" (p.11)

Table 5.6: Gender-gap by activities

	Descriptive stat.				Regressions	
	Obs.	%F.	Average		Female coefficient	
Subsample			LS	RA	in LS	in Loss
all	33,530	0.496	1,018.3	1,384.7	−30.41***	−6.396***
all (with act.)					−26.91***	−4.703**
Peddler	8,840	0.624	822.7	1,126.9	−1.71	−5.434**
Barbershop	1,475	0.754	852.7	1,199.5	4.52	1.995
Clothing	1,449	0.827	860.2	1,245.5	23.01	0.012
Bar/Deli	4,160	0.402	891.4	1,270.2	−4.18	−3.319
Building	1,098	0.153	995.8	1,389.0	−23.54	−13.360
Rent	3,526	0.464	1,159.3	1,431.0	0.98	−3.036*
Transport	2,178	0.166	1,132.2	1,462.0	−32.46	−6.318
Other act.	4,649	0.429	1,100.5	1,516.2	−38.99 **	−9.283*
Other serv.	1,171	0.381	1,136.2	1,650.5	−5.74	−11.690
Artisan	1,081	0.425	1,333.8	1,774.8	−68.62*	−17.370
School	568	0.791	1,339.5	1,813.2	−111.1 **	−40.980
Shop	2,737	0.445	1,375.5	1,839.5	−67.83***	9.554

*** p<0.01, ** p<0.05, * p<0.1

the regression by activity subsample tells another story. The loan size is significantly different among gender only for activities with bigger scale. The significance of the gender dummy is not related to the proportion of women in each activity nor to the significance of the gender dummy in the loss regression. Thus, the gender gap does not seem to be a question of sector (more or less feminin with more or less potential collateral ...) but a question of scale. This question will be adressed more specifically in the next chapter.

5.6 Conclusion

Study the existence and possible economic justification of discrimination, is not only a question of ethics but of efficiency as well. Even when an MFI is not for profit, its resources are limited and need to be allocated in the most efficient way to guaranty its sustainability and clients attendance in the long term.

The empirical approach to discrimination in the lending industry is less clear-cut than in the labor market. Indeed, there are large methodological variations, mainly data driven, in the literature. First, several explained variables are considered: denial rate, interest rate, collateral requirements, etc. Second, creditworthiness is assessed in different ways. Logically, severe criticisms on that literature have warned against premature interpretation in terms of discriminatory practices. Nevertheless, the MFI under study uses a lending methodology based on fixed interest and no collateral, allowing to focus on loan size as the main relevant credit condition.

In this perspective, the present chapter compares the repayment behavior of Vivacred male and female clients, taking in account (Heckman procedure) a potential selection bias induced by the committee approval or denial. In accordance with the previous chapter, women benefit from fair access to credit, but suffer from a small loan downsizing comparing to their male counterpart. This outcome is neither economically justified, nor tampered by relationship.

Women repay better than men: their probability of delay and default as well as the loss amount is smaller for women than for men with the same loan size. Our results are consistent with Armendáriz & Morduch (2010) reporting that women receive smaller loans and repay swiftly than men. Nonetheless, our results are more suited to detect discrimination as we are able to control for required amount and loan size.

Furthermore, gender-gap in loan size is increasing along the loan renewal (female repayment continuing to be better) whereas one could expect it to decrease with asymmetric information dwindling. Extending the analysis to all the people involved in the loan (spouse or external guarantor), we find that an additional male protagonist provide an additional amount of loan while a female one does not.

While our regressions are based on all available variables (considered by the committee), we cannot exclude that face-to-face interviews bring additional gender-related informations absent from our database. Nevertheless, evidences are strongly advocating to cultural habits explanation of observed gender-gap. Businesswomen are not taken seriously.

Do women repay better because they fear more penalties, an hypothesis compatible with evidence that women are more risk-averse (see, e.g. Borghans et al. (2009), or do they behave in a more strategical way hoping higher subsequent loans in the future? Do women expect to be discriminated against and adapt by requesting smaller loans? Do female micro-entrepreneurs refrain from applying for risky project so that self-selection is at stake? To which extent do household constraints interact with their business preoccupations? Qualitative interview-based research could be an asset to better understand the factors that drive the female borrowers behavior. Addressing these questions could lead to designing gender-conscious financial products.

One could classify gender-gap sources in three category: actual distaste, unjustified belief or rationnal knowledge that female would be more risky than male. In the present case, gender-gap is certainly not a question of distaste from the entier institution as disparate treatement would be uniformally oberved among women and would probably affect the probability of approval. The gender gap seem to be consentrated in higher scale activities, pointing out a possible lack of credibility for biggest projets holded by women.

Next chapter explore the project's scale aspect of gender-gap. It addresses as well the question of potential "gender afinity" through this lens.