4 Who is responsible for Gender-specific Loan Size?

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4.1 Introduction

Chapter 3 exhibits an important role played by the credit officer in loan performance mainly at the selection stage. On one hand, career management has a role to play in order to promote field experience and improve the institution efficiency. On the other hand, as are not simple implementers of the institution methodology, their autonomy can leave a space to express their prejudice. Chapter 4 documents the existence of a gender-gap in loan attribution disentangling request and provision sides' responsibilities. Chapter 5 analyses whether this gap is economically justified. Finally chapter 6 explores the non-linearities of this gender-specific treatment uncovering the existence of a glass ceiling for more ambitious women.

Up to now, Labie et al. (2010), little attention has been paid to discrimination in the microfinance industry. The sector is often viewed as a tool for women empowerment, as if it were the place for some sort of spontaneous affirmative action. In that line of thought, gender-discrimination is not even considered as a possibility. Nevertheless, that view is over-simplistic. Indeed, the fact that women in developing countries are poorer than men on average (Medeiros & Costa (2008)) does by no means imply that the Microfinance Institutions (MFIs) serve them fairly.

The literature on discrimination in the lending sector makes a clear distinction between the - typically binary - variables that allow for testing the presence of discrimination and the determinants of creditworthiness. On the contrary, the microfinance literature often uses gender and race dummy variables as proxies for poverty, making *de facto* impossible to test for discriminatory practices in microcredit allocation. Moreover, it has been widely recognized that microfinance institutions tend to offer smaller loans to women who, in turn, reimburse better.

Because gender-specific treatment in lending could be associated not only with poverty but could be hiding other reasons, this chapter analyzes the loan attribution process in terms of access and loan size, by first applying the classical "discrimination-in-lending" methodology to the microcredit industry. Moreover, thanks to the unique database provided by Vivacred, we are able to distinguish responsibilities between client's request, credit officer's proposition and committee attribution, regarding the existing gender-gap.

Discrimination in microcredit conditions has not been tested so far. Nevertheless, the link between microfinance practices and women empowerment has been thoroughly examined. On the one hand, several authors have acknowledged the merits of microfinance on increasing the women's bargaining power and social capital Hashemi et al. (1996); Pitt et al. (2006).On the other hand, in line with Goetz & Gupta (1996), recent studies on intra-household relations in India Garikipati (2008); Guérin et al. (2009) have challenged the impact of microfinance on women empowerment by exhibiting that lending to women may increase their financial vulnerability. Trying to reconcile both views, Kabeer (2001) observes that the positive evaluations focus on access to credit while the negative ones focus on loan use. She concludes by emphasizing that the reasons for lending to women go far beyond empowerment. Scrutinizing the sector's lending practices may thus bring valuable insights to this lively debate.

In industrialized countries, gender discrimination has been detected in various economic activities. Women are strongly penalized on the job market Altonji et al. (1999); Blau & Kahn (2000),(Altonji and Blank, 1999; testifying that competition is largely insufficient to deter discriminatory practices. Evidence is also found in other fields, like car market Ayres & Siegelman (1995) and housing market Yinger (1986); Page (1995). As social psychologists claim Fein & Spencer (1997); Kunda & Sinclair (1999), stereotyping and prejudice are common features in human behavior. Gender discrimination, as a subset thereof, is potentially located in every decision. Unfortunately, in most fields, data are often insufficient to test for it.[1]

Because of US legal requirements[2], race and gender discrimination has

[1]A report by the US Government Accountability Office acknowledges that "most research suggests that discrimination may play a role in certain types of non mortgage lending, but data limitations complicate efforts by researchers and regulators to better understand this issue" (Williams (2008),GAO, p.1) Actually, the problem presumably extends to a large variety of situations where decision-makers observe personal characteristics irrelevant to the purpose of their task.

[2] The US legal framework against discrimination in lending notably includes the Fair

been scrutinized in both the mortgage lending Munnell et al. (1996); Turner & Skidmore (1999); Han (2004) and the small business credit industry Blanchflower et al. (2003); Cavalluzzo & Cavalluzzo (1998); Cavalluzzo & Wolken (2005). In mortgage lending, evidence shows that black applicants face the worst denial rate Schafer & Ladd (1982); Ross & Yinger (2002) while female applicants are subject to disparate treatment Ladd (1998). Refining the existing econometric methodology, Blanchard et al. (2008) also find evidence of discrimination in lending against black-owned and Hispanic-owned businesses, but none against white woman. However, these authors do not separate black and Hispanic by gender, which makes it difficult to globally assess discrimination against female applicants.

Stereotypes thus seem to survive the enforcement of the US Equal Credit Opportunity Act. Elsewhere, the issue has been scarcely studied. Storey (2004) shows that, in Trinidad and Tobago, loan applications from African small-business owners are more likely to be denied than others. A study on Italian microfirms and self-employed individuals by Alesina et al. (2008) emphasizes that women pay higher interest rates although they exhibit a slightly better credit history. Additional evidence on gender discrimination in Italian small business lending is provided by Bellucci et al. (2009).

By using partial-least-square estimation, we detect no discriminatory practice in the approval rate, but uncover loan size difference between genders. Furthermore, we show that the responsibility for female loan downsizing is attributable to prejudiced credit officers (27.3%) and branch managers (7.4%), but also, to women themselves (65.3%) as, all things equal, they request significantly smaller loans than men do.

The paper is organized as follows. Section 4.2 describes the database. Section 4.3 presents the Partial Least Square estimation method and investigates the impact of gender on loan approval and loan size, taking into account a large spectrum of control variables. Section 4.4 scrutinizes the loan allocation process in order to identify each actor's responsibility in female loan downsizing. Section 4.5 concludes.

housing Act of 1968, the Equal Credit Opportunity Act (ECOA) of 1974 and the Home Mortgage Disclosure Act (HMDA) of 1975. In 1989, the Congress amended the former HMDA and imposed to lenders to report the race and ethnicity of their loan applicants. Wide disparities in the loan denial rates were subsequently exhibited by the Boston Federal Reserve Bank using the HMDA database. Based on denial rates, Munnell et al. (1996) show that ethnic minorities (African-Americans and Hispanic-Americans) were facing much larger loan rejection rates than white applicants with similar creditworthiness characteristics.

4.2 Data

The dataset used in this section contains not only the actual loan contracts (used in chapter 3) but includes, more generally, all the applications presented to the committee (approved or denied). For the period under consideration (1997-2007), about 41,000 loans were solicited by 15,400 applicants, and about 32,000 loans were granted to 11,400 borrowers. Our database includes all pieces of information gathered by the six branches of Vivacred. However, we removed from the data set the applications canceled by the clients, the contracts with incomplete specifications, the loans to Vivacred's employees, and the few group loans. Therefore, the study is based on exhaustive data of 34,000 applications and 32,000 actual loans.

A detailed information is collected by the credit officer for each application. In each case, we know the personal situation and household's budget for the client and the guarantor[3] the business characteristics and financial statements[4], and all credit conditions (loan size, duration, full credit history).

Vivacred is accessible to candidates having at least six months of business activity. The application is examined by the credit committee that makes the final decision (acceptance or denial, and loan size) on the basis of a proposal from the credit officer in charge. Vivacred follows a lending technology based on credit rationing (Stiglitz & Weiss (1981)) rather than on risk-adjusted interest rates (applying a flat interest rate). This way of doing, typical from MFIs, raises ethical issues, as discussed by Hudon (2009).

The term "credit committee", borrowed from Vivacred practice, is misleading. Actually, it refers to a single person. Depending on the requested amount, it can be the branch manager or a senior credit officer (different from the one presenting the loan application to the committee). This definition is an important element for this chapter as we are assessing committee responsibility (among others) in the approval process. Results could not be read in

[3]More precisely, the information available for all clients includes: private and professional addresses, birth date, birth state, marital status, gender, dependent(s), profession, bank references, partner's ID, current account, family consumption, family external income, full credit history (as a borrower, a borrower's partner, or a guarantor). Unfortunately, the Vivacred database does not contain racial information. Actually, because of miscegenation, racial segmentation is difficult in Brazil (Sheriff (2000)). The region of origin, provided for about two-third of Vivacred's clients, could be taken as an imperfect proxy for race (colored people are more concentrated in northern regions). We decided to discard this imprecise information in order not to lose observations.

[4]Namely: location, type of activity, age, bank references, legal status, detailed asset and liability, expenditure and revenues, number of employees.

the same way if it was composed of several members.

Figure 4.1: Vivacred's annual loan volume in gross and deflated terms

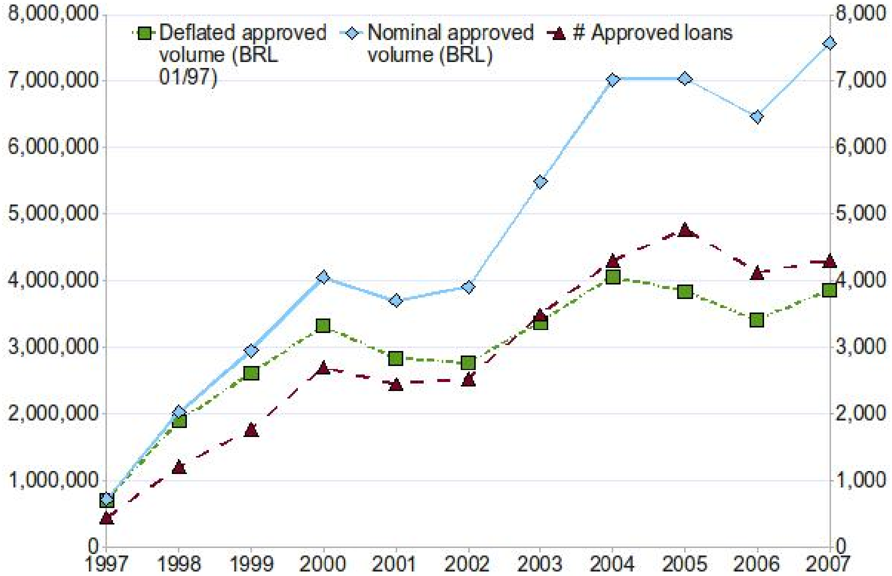


Figure 4.1 presents the evolution of Vivacred portfolio in nominal and deflated BRL[5], respectively. In 1997, microcredit was only starting in Brazil[6]. In 2000-2001, Vivacred experienced a deep staff shortage because of massively headhunting. Thus, the portfolio knew a rise in overall delay and default due to lack of credit officers in 2000-2001 and a decrease in new contracts because of staff hiring and training processes in 2001-2002.

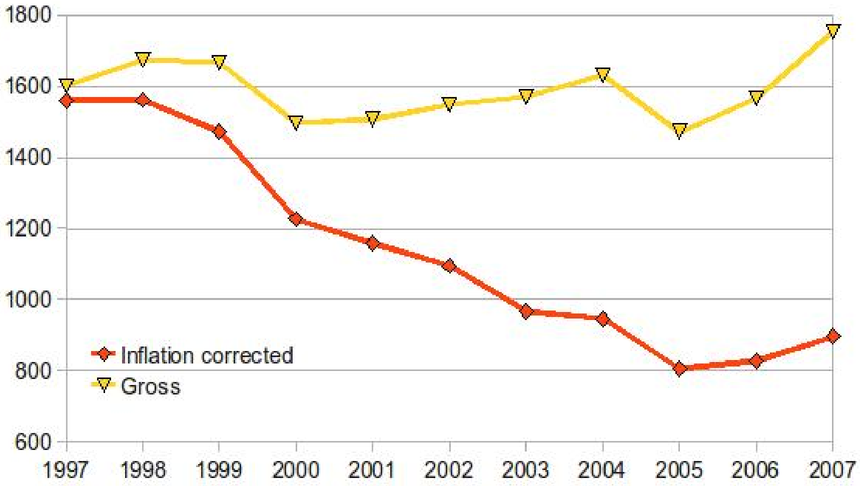
Figure 4.2 depicts the evolution of average loan size in nominal and deflated BRL. The nominal average loan size is stable over the period and thus the deflated loan size is decreasing (from BRL 1,600 in 1997 to BRL 900 in 2007) testifying that Vivacred reinforced its mission fulfillment rather than experiencing a mission drift, like several MFIs in Latin America.

At every moment, an application has a single status among the following ones: 1) untreated, 2) canceled by the client, 3) under the credit officer's examination, 4) denied by the credit committee, 5) accepted by the credit committee, 6) on-going repayment, 7) in recovery, 8) fully repaid, and 9) in loss. A repayment is considered as "delayed" after 30 days, and as "defaulted" after 180 days. The penalty for default is the client's name inclusion within

[5]BRL denotes the Brazilian currency (Real). Over the period under consideration, the BRL fluctuated between 0.270 and 0.588 USD.

[6]Until 2005, Brazilian authorities made no distinction between credit for consumption and for business.

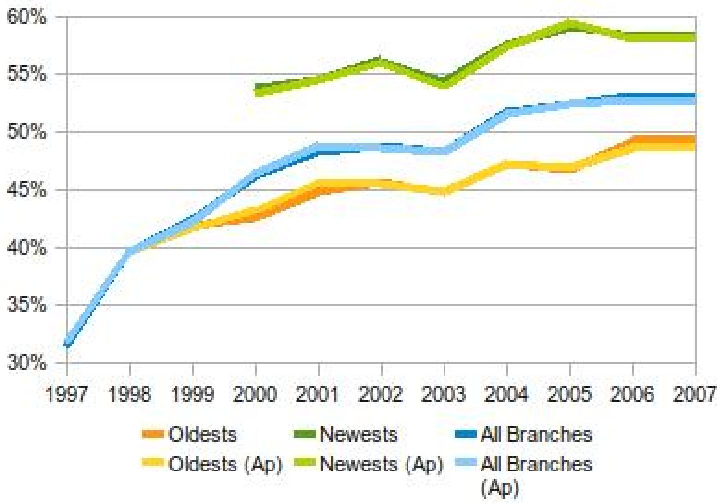
Figure 4.2: Vivacred's gross and deflated average loan size



SPC register[7], which is available for consultation by any institution supplying any kind of credit, including shops. The penalty for default is thus significant. Beyond losing access to credit, those who are registered in SPC face serious trouble getting a cell phone contract or buying household appliances, for example.

Table 4.1 provides the descriptive statistics for all client's characteristics, globally and split by gender, together with a t-test for equal mean among the two groups.

Figure 4.3: Female share evolution in loans and applications.



Vivacred claims no special focus on female population. Its clientele is balanced with 49,6% of loans attributed to women over the period 1997-2007.

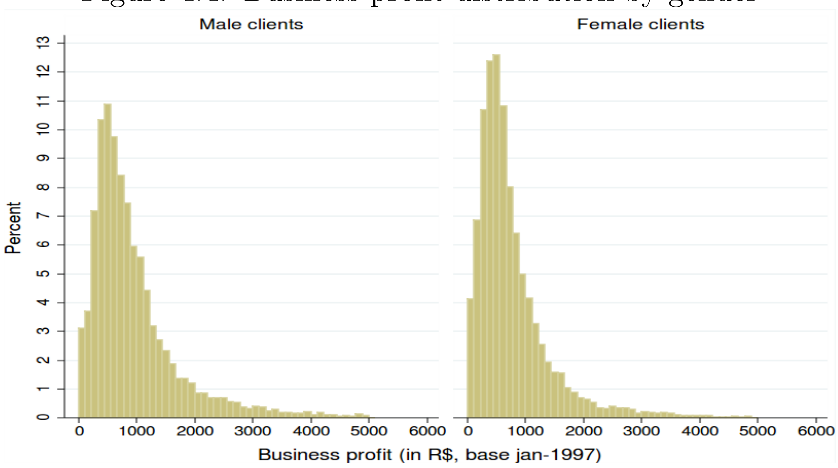
[7]SPC is a national database recording all the late payments declared by any institution delivering any kind of credit (including hire purchase).

Figure 4.3 shows that the proportion of female clients and applicants steadily increased over time[8], rising from 32% to 53%, which is consistent with the average loan size decrease[9]. This increase in female proportion is due both to an increase within the two oldest branches and a higher proportion of women attended in the four newest branches since they opened.

Moreover, female applicants are on average two years older than males (45 versus 43), less likely to be married (43% versus 52%), and less likely to have dependents (51% versus 53%).

Vivacred's male and female clients differ not only in their personal situation, but also in their business characteristics. Indeed, table 4.1 shows that the female-owned businesses are typically smaller, both in terms of receipts and expenses, and in terms of staff size. Business profit distribution by gender is presented in figure 4.4. The distribution exhibits a narrower shape toward zero, and consequently a smaller average profit for female than for male. The external income (i.e., earned by any household member and not related to the business activity) is similar among genders (around BRL 210 a month).

Figure 4.4: Business profit distribution by gender



Genders may have different access to alternative funding that would lead to difference in repayment behavior. Table 4.1 shows that women are more likely to hold a current account than men (7.4% against 6.1%). We are not able to distinguish if the current account ownership is a bad proxy to measure alternative funding access or if there is actually no discipline effect on repayment behavior[10].

[8]A similar trend was observed for the Grameen bank by Khandker et al. (1995).
[9]The mainstream microfinance literature considers gender as a proxy for income and justifies MFIs' focus on women as a tool for poverty alleviation.
[10]As this variable represents few clients and is not significant in the regressions presented below, it was ignored in the reported results.

T-tests comparing credit characteristics and outcomes among genders, in table 4.1, confirm significant differences. Women ask for smaller loans (BRL 1,254 versus BRL 1,526 for men) to be payed back in less installments. Capital investment represents 34% of the loans for male and 29% for female clients. Thus, female loans are more frequently motivated by liquidity issues. Guarantor's and client's gender are unrelated. Men and women face similar approval rates (about 95%), but women receive from smaller loans, in absolute terms (BRL 846 versus BRL 1074) as well as proportionately to the requested amount (73.7% versus 74.7%).

Table 4.1: Global and gender-disaggregated descriptive statistics

	Global Mean	**Std. Dev.**	**Mean Male**	**Mean Female**	**t-test**[c]
Female client (Yes = 1, No = 0)	0.496	0.50			
Loan approval (Yes = 1, No = 0)	0.945	0.228	0.944	0.946	−0.00213
Requested amount (X 100 BRL[a])	13.92	12.42	15.26	12.54	2.722***
Loan size (X 100 BRL[a])	9.61	9.98	10.74	8.46	2.282***
Client profile					
Age (in years)	42.20	11.97	41.24	43.17	−1.925***
Married (Yes = 1, No = 0)	0.47	0.50	0.52	0.43	0.0962***
At least one dependent (Yes = 1, No = 0)	0.52	0.50	0.53	0.51	0.0169**
External income (X 100 BRL[a])	2.13	3.76	2.11	2.16	−0.04
Current account holder (Yes = 1, No = 0)	0.068	0.21	0.061	0.074	−0.0131***
Home-to-branch distance[b] (in kilometers)	5.42	13.91	5.55	5.29	0.25
# former loans at Vivacred	2.25	3.27	2.35	2.15	0.202***
# former loans with delay (> 30 days)	0.038	0.205	0.043	0.035	0.0077***
# times as a guarantor	0.74	2.11	0.89	0.6	0.282***
Business characteristics					
Business profit (X 100 BRL[a])	9.19	13.44	10.26	8.09	2.177***
Sector (trade = 1, other = 0)	0.53	0.50	0.49	0.56	−0.0760***
Official business (Yes = 1, No = 0)	0.06	0.23	0.07	0.05	0.0165***
# employees	0.63	2.20	0.72	0.54	0.175***
Credit characteristics					
# of installments	9.03	4.39	9.1	8.97	0.128**
Capital investment purpose (Yes = 1, No = 0)	0.32	0.47	0.34	0.29	0.0518***
Loan repayment purpose (Yes = 1, No = 0)	0.09	0.29	0.08	0.1	−0.0171***
Guarantor's involvement (Yes = 1, No = 0)	0.92	0.27	0.93	0.92	0.00756**
Male guarantor[b] (Yes = 1, No = 0)	0.57	0.50	0.57	0.57	0.00106
Observations		33,850			

[a]In 100 BRL corrected from the Rio de Janeiro state inflation index - IPC.
[b]Available on a subsample: guarantor's gender (n=31,319), distance (n=29,478)
[c]t-test for equal means between genders; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Different possible channels can explain gender-gap in loan conditions, among which: a difference of initial situation (business scale, guarantee ...), kind of activity more or less profitable, with more or less easily seizable equipment, difference of requests or ambitions or even an actual difference of treatment among genders. Gender-gap sources can be classified in three completely different categories: 1) it can be due to an actual distaste from the lender, 2) to an unjustified belief from the lender that women are less able or more risky than men, or finally 3) it can be based on an actual knowledge that female would be more risky than male.

The next section will further investigate the loan approval probability and the loan size determination checking whether the findings from basic equal-mean tests resist the inclusion of explanatory variables meant to proxy creditworthiness.

4.3 Gender-specific Approval and Loan Size

Microfinance literature has widely acknowledged that, on average, women receive smaller loans than men Morduch (1999). Authors often rationalize this evidence as a sign that women are poorer and, therefore, require smaller loans. Nevertheless, if women are not less able by nature, then the conclusion that they need smaller loans should not resist the inclusion of control variables accounting for poverty level in the regression.

Considering gender as a proxy for poverty may be seen as acknowledging the existence of omitted variables in the regressions Choi et al. (2008). In that perspective, if credit officers are using gender as a proxy for creditworthiness, thus for economic reasons and not because of their prejudice, then it would mean that statistical discrimination takes place in MFIs. However, discrimination, even statistical, is recognized not to be ethical and prohibited under the US legal framework.

Differences in denial rates is the cornerstone of the empirical literature on discrimination in the lending industry. The standard method goes as follows: if regressing denial on the gender dummy and appropriate controls produces a significant gender coefficient, then discrimination is suspected. Indeed, this would mean that, all other things being equal, one gender is facing more severe loan approval than the other. This way of testing for race, gender, and ethnicity discrimination has been largely used. Depending on data availability, credit conditions (notably, the interest rate[11]) have been examined along the same way[12].

[11]In our case, interest rate is pointless since Vivacred charge the same for all its loans.
[12]See Lacour-Little (1999) for a survey on models and methods on discrimination in mortgage lending, and Blanchard et al. (2008) for a survey on discrimination in lending to small businesses.

Our empirical investigation starts with this methodology. Our database allows considering two explained variables: loan approval and loan size (denial being the special case of zero loan). For the approval probability (A_i=1 if applicant i gets a loan, A_i=0 otherwise), we estimate the following probit model:

$$P(A_i = 1) = \Phi(b_F\, F_i + b_R\, RA_i + \mathbf{b}'_\mathbf{Z}\, \mathbf{Z_i}) \tag{4-1}$$

where $\Phi(.)$ represents the normal probability distribution function, F_i is the gender dummy variable (F_i=1 if applicant i is a woman), RA_i is the amount requested by applicant i, $\mathbf{Z_i}$[13] is the vector summarizing the J control variables for applicant i. The corresponding coefficients are b_F, b_R, and vector $\mathbf{b_Z}$, respectively.

A standard ordinary-least-squares (OLS) regression model including the same independent variables is used for explaining the loan size:

$$LS_i = c_F F_i + c_R\, RA_i + \mathbf{c}'_\mathbf{Z}\, \mathbf{Z_i} + \epsilon_i \tag{4-2}$$

where LS_i represents the loan size[14] obtained by applicant i. The coefficients associated to the independent variables are denoted by c_F, c_R, and vector $\mathbf{c_Z}$, respectively.

Unlike mortgage loans that are typically approved or denied, productive loans can be easily sized by the lender. Therefore, the requested amount is a relevant piece of information that allows detecting credit rationing. Fortunately, our wealthy data base includes all applicants' requests. Thanks to those data, we can determine whether gender-specific approval and loan size are due exclusively to gender-specific requested amount or not. Requested amount is a non-standard explanatory variable in the literature on discrimination in lending, probably because of data availability issues.

The control variables are the ones typically used to assess creditworthiness. They include the borrower's personal information (age, marital status, external income, presence of dependents, guarantor's involvement and gender if involved), the business characteristics (past profits, sector, whether the business is official, number of employees), the credit characteristics (number of installments and loan purpose), as well as the client's credit history with Vivacred (delays in previous loans, number of former loans as a client and as a guarantor). Year dummies are introduced in order to account for external

[13] All bold typed elements are vectors.
[14] Denied applications are not excluded but captured by a zero loan size.

economic factors.

Blanchard et al. (2005) recommend to add the distance to the branch as a control variable. Unfortunately, our dataset provides this information for a subsample only (87% of the loans). After having checked on this subsample that the distance, although significant, does not interact with the other regression coefficients (results not reported), we decided to exclude this control in order not to lose the observations with missing distance.

Table 4.2: Loan approval (Yes=1, No=0) probit regression

Loan approval	(1) Coeff.	Marg. effect	(2) Coeff.	Marg. effect	(3) Coeff.	Marg. effect
Female client	0.0267	0.00254	0.0132	0.00123	0.0273	0.00254
	(0.0237)	(0.00225)	(0.0239)	(0.00222)	(0.0238)	(0.00221)
Requested amount (RA)			-1.31e-04***	-1.22e-05***		
			(1.05e-05)	(9.75e-07)		
Residual RA (RRA)					-1.31e-04***	-1.22e-05***
					(1.05e-05)	(9.75e-07)
All controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33850	33850	33850	33850	33850	33850

"Marg. effects" columns report probit marginal effects at the mean. All monetary variables in deflated BRL
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4.2 presents the estimated coefficients[15] and marginal effects at the mean for the probit regression (eq. 4-1). In specification (1), the requested amount (RA_i) is ignored (assuming $b_R = 0$). Specification (2) includes the requested amount. In both cases, the client's gender coefficient is not significant. Therefore, we find no evidence of difference in approval probability faced by male and female applicants. This result confirms the similarity of approval proportion between men and women already uncovered by descriptive statistics (table 4.1).

However, restricting the analysis to approval and denial may hinder more subtle information on credit conditions. Table 4.3 presents the estimation of loan size regression. Like previously, specification (1) excludes the requested amount while specification (2) includes it[16]. The gender effect found in loan size sharply contrasts with the approval rate gender-neutrality. Indeed, table 4.3 exhibits a significantly negative coefficient for the gender dummy meaning that, all other things being equal[17] (including the requested amount), women get smaller loans than men.

[15] Table 4.2 does not report the estimated coefficients for the control variables. These estimates, available upon request, are similar to those given in table 4.3 and commented accordingly in the text.

[16] Alternatively, we could regress the proportion of requested amount approved by the committee (Loan size/Requested amount). In this case, financial controls (extra income and business profit) have to be scaled by the requested amount as well. Such a regression is presented in table B.1 in appendix.

[17] Guarantor income is not available for the period from 1997 to 2004 and thus omitted in

Moreover, the comparison of columns (1) and (2) in table 4.3 highlights the difference in estimation magnitudes. In specification (1), the female dummy coefficient is equal to (-93.45) while in (2) it reaches (-32.43) only. Thus, women do indeed get smaller loans, but largely because, under similar circumstances, they ask for smaller loans than men (request channel).

Table 4.3: Loan size regression (OLS and PLS)

Loan size	OLS (1)	OLS (2)	PLS (3)
Female client	-93.45***	-32.43***	-93.45***
	(8.665)	(5.799)	(5.791)
Requested amount (RA)		0.573***	
		(0.00280)	
Residual RA (RRA)			0.573***
			(0.00280)
Married client	29.16***	7.330	29.16***
	(8.933)	(5.972)	(5.971)
Client with dependent(s)	18.12**	13.65**	18.12***
	(8.986)	(6.006)	(6.006)
Client's age	-2.680***	0.560**	-2.680***
	(0.368)	(0.247)	(0.246)
External income	0.327***	0.111***	0.327***
	(0.0115)	(0.00776)	(0.00769)
# of former loans at Vivacred	47.68***	32.79***	47.68***
	(1.485)	(0.995)	(0.993)
# of times as a guarantor	17.84***	11.10***	17.84***
	(2.130)	(1.424)	(1.423)
# of former loans with delay	-92.70***	-105.7***	-92.70***
	(4.674)	(3.125)	(3.124)
Guarantor involved	220.5***	38.86***	220.5***
	(17.29)	(11.59)	(11.55)
Male Guarantor	99.59***	32.07***	99.59***
	(8.959)	(5.997)	(5.988)
Loan repayment	20.03	93.68***	20.03*
	(15.47)	(10.35)	(10.34)
# of installments	58.01***	21.72***	58.01***
	(0.997)	(0.689)	(0.666)
Capital investment	172.0***	63.18***	172.0***
	(9.722)	(6.520)	(6.498)
Business profit	0.206***	0.0643***	0.206***
	(0.00335)	(0.00234)	(0.00224)
# of employees	44.62***	10.91***	44.62***
	(2.048)	(1.378)	(1.369)
Trade (sector)	-36.86***	-4.234	-36.86***
	(8.973)	(6.000)	(5.997)
Official business	711.3***	193.7***	711.3***
	(19.43)	(13.23)	(12.99)
Constant	196.7***	-313.2***	196.7***
	(43.16)	(28.95)	(28.84)
Year dummy	Yes	Yes	Yes
Observations	33850	33850	33850
R^2	0.390	0.728	0.728

Monetary variables are measured in deflated BRL
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

these regressions. Nonetheless, table B.2 in appendix presents the OLS and PLS regressions by period (1997-2004 and 2005-2007), with and without guarantor income as a control for the second period. Even if female dummy coefficient is slightly smaller, when including guarantor income, it remains strongly significant.

As shown by table 4.1, the requested amount is gender-sensitive. Women request on average BRL $1,254$, while men request on average BRL $1,526$[18]. In order to examine whether this gender-specificity remains when the control variables enter the picture, we regressed the requested amount on the gender dummy and controls. The regression (not reported here) provides significant estimates for the gender dummy (a female applicant's request lies BRL 107 below the one of a male applicant with similar characteristics)[19].

From an econometric point of view, specification (1) suffers from an omitted variable problem as the requested amount is absent. Thus, female dummy capture the gender effect both through the direct and the requested amount channels. Specification (2) distinguishes between the two channels. Female dummy coefficient is affected in both equations 4-1 and 4-2[20].

In order to properly identify the different channels through which gender affect the loan size, we implement a Partial Least Square (PLS) estimation procedure Wold et al. (1984); Tenenhaus (1998); Helland (1990) allowing for disentangling the effects of request and provision decision in loan size.

In practice, loan size determination results from a sequential process: First, the applicant makes a loan request RA_i, then the MFI offers a loan of size LS_i. Therefore, the PLS method is adequate as it rests upon a recursive specification. In the first step, we regress the requested amount on the gender dummy and the control variables, and determine the residual requested amount, denoted by RRA_i:

$$RA_i = a_F F_i + \mathbf{a}'_{\mathbf{Z}} \mathbf{Z_i} + RRA_i \tag{4-3}$$

Thus, RRA_i represents the "pure" request effect emanating from candidate i, excluding the impacts of gender and controls. In the second step, we explain the loan approval probability, respectively the loan size, by the gender dummy, the controls and the residual requested amount. The loan approval probability[21] becomes:

[18]We ignore why female applicants act in this way and whether they expect a gender-specific treatment from the institution's decisions. It could be the case that, although in similar conditions, women have different business ambitions than men or have a different perception of indebtedness risk. Indeed, women are known to exhibit more risk aversion than men in financial decision making Jianakopolos & Bernasek (1998)

[19]In the raw data (table 4.1), the difference amounted BRL 272.

[20]This multiple channels problem is not mentioned in other papers, most probably because the data made available to the researchers usually excludes the applicant's requests.

[21]PLS is normally designed for linear regression but we adapt it to probit regression. By doing so, we might distort to some extent the marginal effects but the significance thresholds remain adequate, which is the main concern here.

$$P(A_i = 1) = \Phi[(b_F + b_R a_F)F_i + (\mathbf{b'_Z} + b_R \mathbf{a'_Z})\mathbf{Z_i} + b_R\, RRA_i] \quad (4\text{-}4)$$

Similarly, the PLS loan size regression writes:

$$LS_i = (c_F + c_R a_F)F_i + (\mathbf{c'_Z} + c_R \mathbf{a'_Z})\mathbf{Z_i} + c_R\, RRA_i + \epsilon_i \quad (4\text{-}5)$$

Combining estimated coefficient from equation (4-3) with (4-4) or (4-5), we are able to construct a pure effect from requested amount without mixing with gender and controls. In equations (4-4) and (4-5), the gender dummy coefficients have two parts. For instance, in equation (4-5) the term $c_R a_F$ depicts the request channel of gender effect on loan size (effect attributable the female applicants request in loan size difference between genders), while c_F represents the provision effect to be interpreted, if significant, as a piece of evidence for discrimination. The gender dummy coefficient in equation (4-5) captures both effects. Nonetheless, the knowledge of coefficients a_F from equation (4-3) and c_R from the residual request term in equation (4-5) makes it possible to disentangle the two parts. In that way, we allocate to the female applicants and to the MFI their respective shares of responsibility for women getting smaller loans.

PLS regression results are reported in column (3) of table 4.2 for the loan approval, and in column (3) of table 4.3 for the loan size. The client's gender coefficient remains insignificant in the loan approval regression. Thus, men and women have the same probability to get a loan, even after considering the channels issue.

In the loan size regression not only does the gender dummy coefficient remain significantly negative, but also its point estimate increases in comparison with respect to specification (2) as it gets back to the value reached in specification (1)[22]. Table 4.1 reveals that average loan size is BRL 961. According to the PLS regression in table 4.3, a female client receives BRL 93.5 (9.7% of the average loan size) less than a male with similar characteristics.

The comparison of columns (2) and (3) in table 4.3 confirms the relevance of channels concern. Indeed, the OLS estimate of the gender dummy

[22]This result was to be expected as specification (1) excludes the requested amount from the set of explanatory variable while specification (3) excludes gender-based requested amount. However, specification (3) is more adequate than (1) because it solves the omitted variable problem by taking into account the request impact through the coefficients associated to the residual requested amount and the control variables. The direct consequence of this correction is a standard errors reduction. The R^2 is much higher too in (3) as compared to (1), testifying that the residual requested amount has important explanatory power.

coefficient is only one third of the PLS one. Therefore, we conclude that the gender difference in loan sizes is attributable for 33% to provision decision and for 67% to client request[23]. Because they request more modest loans, women are responsible for about two thirds of the resulting loan shrinkage, but the remaining third is still attributable to MFI practices (potentially discriminatory). All other things being equal (including the requested amount), the MFI allocates smaller loans to female applicants.

Moreover, personal characteristics, although significant, have a small impact on loan size. Being married, having at least one dependent, and being ten years younger provide, respectively, an additional loan size of BRL 29, 18 and 27, each representing less than 3% of the average loan size. The household external income acts as an informal collateral. A client earning the average external income (BRL 213) gets BRL 70 more than his/her counterpart without any external income.

The client's relationship intensity appears in the regression through three integer variables representing, respectively, the number of former loans in Vivacred as a client, as a guarantor, and the number of loans with more than 30 days of repayment delay. The gain associated to a timely repaid loan (BRL 47.7) in credit history is equivalent to the loss resulting from a lately repaid loan (BRL 45)[24]. The impact of the client's history as a guarantor is less pronounced (one fourth of the impact of a former loan as a client).

A guarantor's involvement seem to have a huge impact on loan size (an additional BRL 220.5). This result has to be mitigated by the fact that such involvement is almost systematic at Vivacred (93% of the loans). Guarantor is not required for client with good credit history asking for small complementary loans. More interestingly, a male guarantor provides on average a BRL 99.6 loan size advantage comparing to a female one. As this amount is approximately equal to the female borrower's penalty, a woman benefiting from a male guarantor is treated in the same way as a man with a female guarantor. On the opposite, a female borrower associated to a female guarantor receives BRL 193.1 less than a male-male combination[25].

[23] The gender dummy estimated coefficient in the requested amount regression is $a_F = 107.2$ and the coefficient of residual requested amount in the regression of loan size is $c_R = 0.574$. As the coefficient of the gender dummy in the PLS regression is $(c_F + c_R a_F) = -93.73$, we deduce that 33% of gender dummy coefficient in the loan size PLS regression.

[24] The lately repayment penalty is computed by adding up the positive effect of a former credit (BRL 47.7) and the negative effect of a delayed loan (BRL 92.7)

[25] We failed to detect any significant interaction between the client's and the credit officer's genders (details not reported here).

Coefficients associated to loan's and business's characteristics have the expected signs. Indeed, positive effects are found for the number of installments, for capital investment (compared to treasury needs), and for business size measured by either profits, or staff size. Compared to services, a trade business receives BRL 37 less (4% of the average loan). The infrequent (6% of the sample) loan applications from registered business (official status) are largely favored as they benefit from a premium amounting BRL 711.

In order to check the robustness of gender-gap in loan size, we run loan size regressions by subsample. Table 4.4 resumes the results presenting only the gender dummy coefficient for each regression. The first line depicts the OLS estimation and the second one the PLS estimation. Subsamples are delimited by sector, business scale and loan use. Female dummy, while small, is significant in all cases. According to 5-2 and 4-5, the ratio between the OLS and PLS estimation (F_{OLS}/F_{PLS}) gives us the gender-gap share attributable to provision side (not to request) which is pesente in the following line. This share is about one third in every subsample.

Table 4.4: Female dummy coefficient in OLS and PLS loan size regression

Subsample	Sector		Business Profit			Loan Use	
cut	Trade	No trade	Low π [b]	Med π	High π	Treasury	Invest.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (OLS)	-37.14***	-27.18***	-12.95**	-13.43*	-39.74***	-25.31***	-54.09***
	(9.047)	(7.684)	(6.454)	(7.173)	(15.10)	(6.714)	(11.53)
Female (PLS)	-98.37***	-89.39***	-40.49***	-57.97***	-110.1***	-83.77***	-120.2***
	(9.039)	(7.670)	(6.456)	(7.185)	(15.09)	(6.701)	(11.52)
Provision % [a]	37.76	30.41	31.98	23.17	36.09	30.21	45.00
Observations	16064	17786	11859	12274	9717	23161	10689
R^2	0.692	0.747	0.467	0.588	0.748	0.712	0.730

[a] Share of gender gap in loan size attributable to provision side (not to request) (F_{OLS}/F_{PLS})
[b] Low π: profit<BRL500, Med π: BRL500$\leq$ profit <BRL1000; High π: profit $\geq$BRL1000
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Using a continuous information and not only an approval dummy tells us a much more complete story about gender-gap. Litterature, very often, concludes that discrimination existes when approval is lower for women, ignoring the request side. This early conclusion may lead to inapropriate policy recomendations focusing on provision side when the adequate policy could be focused on female demande, guarantor quality improvement, or on female confidence or ambitions, for example.

The present result make it clear that the main difference in loan size between gencer, once contolled by their characterisitcs, is explained by a difference of request. Deeper investigation to understand this gender-gap in request is needed.

In summary, our analysis has shown that loan approval is not affected by gender consideration, but loan size determination is detrimental to female applicants. The residual gender-gap in loan size explained neither by client characteristics not by a gap of request is small relatively to the average loan size but still positive and significant. However, MFI's responsibility is still a black-box as it join credit officer's propositions and committee provision decision.

4.4 Who is responsible for loan downsizing?

Up to now, loan size determination has been viewed as a two-step process involving the client's request followed by the MFI loan size decision. However, in practice, the loan attribution process within the MFI is more complex. It can be disaggregated in the following way. Once client i has introduced a request for amount RA_i, the credit officer proceeds to a careful file examination, which includes a discussion with the applicant. Then, the officer makes a proposition to the credit committee for the loan size to be attributed to client i, say PA_i. Lastly, the committee examines the full situation (application file and credit officer's proposition) and makes the final decision on loan of size LS_i.

As a matter of fact, the credit officer always has a face-to-face contact with the applicants, while it is not the case for the credit committee (a single person as mentioned above). Officers also spend more time on each individual file. For those reasons, it is likely that discrimination, if any, originates from the officer's side. As our rare database allows for distinguishing between the steps of the procedure, we are able to determine each actor's responsibility in the female loan downsizing.

Table 4.5: Disaggregated loan attribution process (mean values in BRL)

	New applicants			Known applicants		
	M	**F**	**t-test**	**M**	**F**	**t-test**
Requested Amount (RA)	1545.5	1334.0	10.8***	1518.7	1209.4	17.5***
Officer's proposition (PA)	962.5	789.5	12.7***	1260.2	985.5	18.1***
Loan approval rate (LA), (%)	91.2	91.3	−0.18	95.1	95.3	−0.61
Final loan size (LS)	848.9	693.9	11.9***	1190.4	924.6	17.8***
LS/RA	61.7	59.6	3.7***	81.3	81.0	1.0
Obs	6,269	6,231		11,018	10,773	

Table 4.5 presents the gender-specific average requested amount (RA), officer's proposed amount (PA), loan approval rate (LA), final loan size (LS), and loan-size-over-requested-amount ratio (LS/RA). The sample is split in two sub-samples: new applicants and clients who already benefit from a

relationship with Vivacred (at least one former loan). The idea is to check whether gender-specific attendance tend to scale down when the MFI's staff has better knowledge of the applicant. In each case, a t-test for equal means between genders is performed.

While requesting more on average (BRL 1,440 versus BRL 1,366), new applicants face harsher propositions from credit officers (on average, BRL 876 versus BRL 1,124), more denial (9% versus 5%) and smaller loans (BRL 772 versus BRL 1,059), which is consistent with asymmetric information theory. Newcomers receive on average 60.65% of their requested amount, against 81.15% for known clients.

Table 4.5 shows that, whatever their history with Vivacred, women keep equal opportunity to obtain a loan. Strikingly, the gender gaps for requested, proposed amounts and loan size widens with existing relationship. The female-over-male mean value ratios for new applicants are 86.3% for RA, 82% for PA and 81.7% for LS, while the corresponding ratios for known applicants are 79.6%, 78.2%, and 77.7%, respectively. The LS/RA ratio is significantly smaller for women for first loans only. An explanation could be that women learn with time about gender-specific treatment and revise their requests accordingly [26]. As a consequence, gender-specific treatment, while still present at all procedure stages, tend to decrease in raw data.

According to table 4.5, the responsibility for women downsizing is shared by the applicants themselves, the credit officers, and the committee. In order to disentangle the three channels, we use a two-tear PLS estimation method. The regression sequence mimics the actual allocation process.

The first regression explains the requested amount by the gender dummy and the control variables (see eq. 4-3). In the second step, the loan size proposed by the credit officer is regressed on the gender dummy, the controls, and the residual requested amount:

$$PA_i = d_F F_i + \mathbf{d'_Z Z_i} + d_R\, RRA_i + RPA_i \tag{4-6}$$

In that way, we fully incorporate the request effect without distorting the impact of the gender dummy variable. Lastly, we explain the actual loan size resulting from the credit committee's decision by the gender dummy, the

[26] Both men and women tend to reduce their requested amount with experience. However, female applicants reduce it by BRL 124.6 on average while male requests are only BRL 26.8 smaller.

controls, the residual requested amount (due to the client), and the residual proposed amount (due to the officer):

$$LS_i = e_F F_i + \mathbf{e'_Z Z_i} + e_R\, RRA_i + e_P\, RPA_i + \epsilon_i \tag{4-7}$$

This procedure makes it possible to estimate the impact of the requested and proposed amounts independently from the control variables. The remaining gender-related penalty, if any, is then attributable to the credit committee[27]. Indeed, by using the RA_i decomposition in eq.4-3, we obtain:

$$PA_i \;=\; \tilde{d_F} F_i + \tilde{\mathbf{d_Z}}' \mathbf{Z_i} + d_R\, RRA_i + RPA_i \tag{4-8}$$

where

$$\tilde{d_F} \;=\; d_F + d_R a_F \tag{4-9}$$
$$\tilde{\mathbf{d_Z}}' \;=\; \mathbf{d'_Z} + d_R \mathbf{a'_Z} \tag{4-10}$$

Similarly, thanks to eq.4-3 and eq.4-8 the final loan size becomes:

$$LS_i \;=\; \tilde{e_F}\, F_i + \tilde{\mathbf{e_Z}}'\, \mathbf{Z_i} + \tilde{e_R}\, RRA_i + e_P\, RPA_i + \epsilon_i \tag{4-11}$$

where:

$$\tilde{e_F} \;=\; e_F + e_P(d_F + d_R a_F) + e_R a_F \tag{4-12}$$
$$\tilde{\mathbf{e_Z}}' \;=\; \mathbf{e'_Z} + e_P(\mathbf{d'_Z} + d_R \mathbf{a'_Z}) + e_R \mathbf{a'_Z} \tag{4-13}$$
$$\tilde{e_R} \;=\; e_R + e_P d_R \tag{4-14}$$

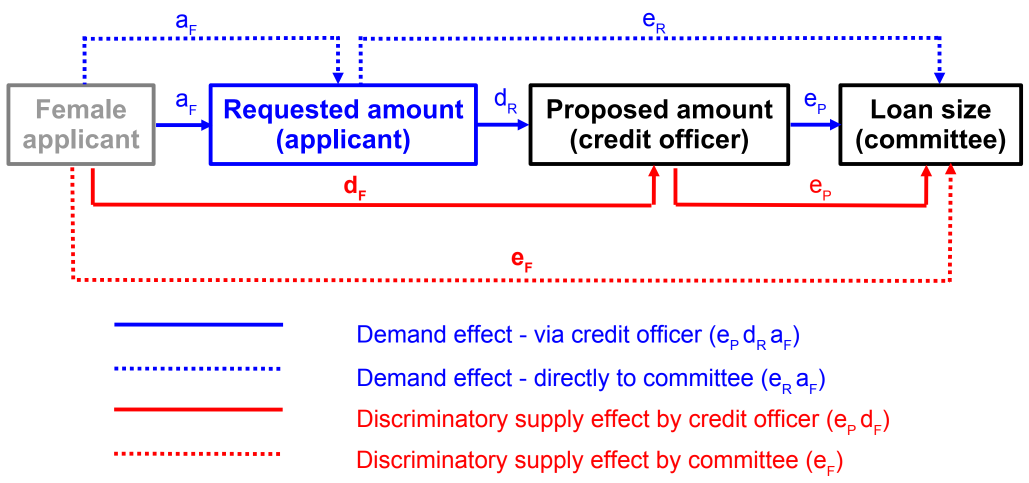
Coefficient $\tilde{e_F}$ is split into four components, each one representing a specific channel through which gender impact the loan size. The committee makes its decision by considering the client's characteristics (including gender and requested amount), and the officer's recommendation. Its decision can thus be gender-related through client's data or officer's recommendation. In the first case, loans provided to a woman may be smaller because the committee observe her request which is more modest ($e_R a_F$) or simply because the committee knows she is a woman (e_F). In the second case, committee decision derive from the officer's downsizing proposition. In turn, the officer's proposition can be either by client request ($e_P d_R a_F$), or based client's gender directly ($e_P d_F$).

[27]As already mentioned, by Vivacred the "credit committee" refers to a single person, the branch manager or a senior credit analyst.

Consequently, the credit committee is potentially contaminated by any of those two sources of downsizing through the officer's proposition.

Figure 4.5 represents these four channels. Blue paths are *chosen* by the female clients (difference in requests), and red paths are *endured* by them (difference attributable to gender discrimination).

Figure 4.5: Decomposition of female loan downsizing (PLS regression)



Section 4.3 has established that two thirds of the gender difference in loan size results from the requested amount and one third results from the allocation decision. The methodology used here allows to go beyond such client-versus-institution analysis and disentangling responsibilities within the MFI. Indeed, the request effect is twofold: direct and channeled by the credit officer. The provision effect also results from the behavior of two actors: the credit officer and the committee.

Table 4.6 reports the two-tears PLS regressions results. Column (1) gives the regression estimates for the requested amount (RA) on gender dummy (F) and controls (eq.4-3), In column (2) the proposed amount (PA) is regressed on gender dummy, residual requested amount (RRA) and controls (eq.4-8). Column (3) explains the loan size (LS) by the gender dummy, the residual requested and proposed amount (RPA), and controls (eq.4-11). The controls' coefficients are not reported.

Women get on average BRL 94 less than men. Table 4.6 allows for decomposing this difference[28]. On the one hand, female request smaller amounts

[28]Indeed, from regression (1) and (2), the estimates are, respectively, 107.2 for a_F,-95.87 for $\tilde{d_F}$, and 0.626. for d_R. From equation 4-9, it follows that the estimate for d_F is -28.76. Then, from regression (3), we obtain the following coefficients:0.889 fore_p, 0.573 for $\tilde{e_R}$,

which, either channeled by the credit officer (BRL 59.66), or coming directly to the committee (BRL 1.77), and on the other hand, to discriminatory practices from the credit officer (BRL 25.57) and from the committee (BRL 6.99).

Table 4.6: Two-tears PLS estimates

	(1)		(2)		(3)	
Dependent variable	RA		PA		LS	
F	-107.2***	(a)	-95.87***	(b)	-93.99***	(d)
	(11.24)		(5.132)		(3.566)	
RRA			0.626***	(c)	0.573***	(e)
			(0.00248)		(0.00173)	
RPA					0.889***	(f)
					(0.00378)	
All controls	Yes		Yes		Yes	
Observations	33850		33850		33850	
R-squared	0.336		0.793		0.897	

Monetary variables in deflated BRL, Standard errors in parentheses, *** p<0.01
(a), (b), (c): Estimators for respectively a_F (eq.4-3), $\tilde{d_F}$ and d_R (eq.4-8)
(d), (e), (f): Estimators for respectively $\tilde{e_F}$, $\tilde{e_R}$ and e_P (eq.4-11)

The repartition of the channels through which gender affects the loan size is presented in table 4.7. The results are given for all applicants (first column), the newcomers (second column), and the known clients (third column). In the full sample, the responsibility for female loan downsizing is attributable to prejudiced credit officers (27.3%) and branch managers (7.4%), but also, to the women themselves (65.3%) as they request significantly smaller loans.

Table 4.7: Responsibility share in Female loan downsizing

	Female applicant's type		
	All	New	Known
Client's responsibility (smaller requested amount):			
Total	65.3%	46.5%	74.1%
- channeled by credit officer	63.5%	44.9%	72.0%
- direct effect on committee	1.8%	1.6%	2.1%
Discriminatory practice (by the institution):			
Total	**34.7%**	**53.5%**	**25.9%**
- by credit officer	27.3%	43.5%	18.1%
- by committee	7.4%	10.0%	7.8%

Discrimination is thus mainly attributable to the credit officers, but the committee adds a marginal contribution. In additional regressions (not reported here), we observed that the officer's gender and marital status do not interact with gender discrimination.

ands -93.99 for $\tilde{e_F}$. Consequently, from equation 4-14, the e_R estimate is 0.0165, and from equation 4-12, since the e_F estimate is -6.99, we compute the following estimated products: $e_P d_F \simeq -25.57$, $e_P d_R a_F \simeq -59.66$, and $e_R a_F \simeq -1.77$.

Disparate treatment is much stronger for a first loan request. However, this observation is mitigated by the fact that women known by the MFI tend to enter smaller loans. This could correspond to female adaptation to borrowing under discriminatory conditions rather than a decrease in discrimination itself. In order words, the learning process is bilateral between the client and the officer, leading to some convergence, but one still ignores who made the largest concession. This issue will be further analyzed by considering the evolution of individual clients history within the MFI in the next chapter. Moreover, the methodology proposed by Han (2004) could help disentangling taste-based and statistical discrimination.

This section shows that discrimination in loan size is mainly attributable to biased credit officers, after correction for all possible sources of non-discriminatory gender-specific element. More surprising is the additional discrimination brought by the credit committee which has no direct relation with the applicants. However, in Vivacred this committee is composed of a single person, making the decision potentially discretionary. We conjecture that the committee reaction is structure-dependent and that larger committees would be less inclined to discriminate, or would even act against the credit officer's prejudice and restore at least some fairness in loan allocation.

4.5 Conclusion

This chapter confirms Corsi et al. (2006) results that a gender-sensitive approach makes sense in the microfinance industry. The lack of evidence about discriminatory loan approval is an encouraging result, especially given the persistent inequality by race observed in denial rates in the US banking sector Weller (2009).

Unfortunately, we do not observe the very first step of the loan process: before an application reaches the committee. One one hand, we do not observe the client application decision, and on the other hand, the data are poorly depicting registered applications that did not reach the committee. We do not know precisely what happened: disclaim, inadequate application, lack of guarantor... These applications are excluded from the database. The first contact with the institution is determinant to proceed or to be to discourage.

Literature traditionally assesses discrimination using only this binary information. This chapter shows that it is insufficient and provides a continuous analysis using the approved loan size. Two thirds of the loan size difference between female and male clients are due to a difference of requested amount which is smaller for women.

Several explanations for this difference in requirement are plausible: First, men and women can handle different projects and thus have different financial needs. However, we are controlling for the business size, the sector and the use of the loan (treasury or investment). Thus, financial needs should not be affected so much by the client gender. Second, women may have a greater risk aversion than men (as depicted in the financial psychology literature) and thus require only what is strictly necessary. Third, women can anticipate the downsizing and thus choose less ambitious projects. The next section provides some evidence in accordance with this third scenario: along the relationship (loan renewal), amounts requested grow much slower when requested by women.

Furthermore, the remaining third of gender-gap in loan size (not related to requirement) comes from the institution's decisions. Fortunately, the data provide great details about the loan process, compared to the empirical literature, including the amount required by the applicant, recommended by the credit officer to the committee and the actual loan size approved by the committee. The credit officer is actually responsible for the main part of this institutional share (comparing to committee).

This chapter is a warning about the danger of considering gender dummy as an appropriate proxy for poverty which would justify smaller project and thus smaller loan for female. Poverty argument can hide potential discrimination. Viewed through the women empowerment lens, our results are consistent with two dominant, but seemingly contradictory, features found in the literature. On the one hand, as far as access to credit is concerned, women are indeed treated on the same grounds as men. Therefore, microcredit does indeed offer unexplored opportunities to female entrepreneurs. But on the other hand, women keep facing harder conditions than men, not only regarding their social and familial status, but also regarding the conditions of their loans. In this perspective, our results extend to credit conditions the mitigated conclusions on women empowerment reached by Kabeer (2001).

A wide literature stream on entrepreneurship in developed countries points that female entrepreneurs tend to be less financed (see, e.g., Riding & Swift (1990) for Canada, Verheul & Thurik (2001) for the Netherlands, Alsos et al. (2006) for Norway). It is therefore little surprise that the same is observed in developing countries. Although microfinance sector has the great merit of having brought into light the underestimated potential for female entrepreneurship, it is not *per se* free from discriminatory practices.

Next chapter assesses the impact of gender on creditworthiness through a careful examination of default history Ferguson & Peters (1995). If women do indeed exhibit lower default rates, as often claimed by the microcredit industry and confirmed by Marrez & Schmit (2009) study on a Moroccan MFI, then the presence of taste discrimination, as opposed to profit-based statistical discrimination, would become undeniable. As pointed out by Ladd (1998), very little information exists on default rate. Therefore, we strongly encourage regulators, donors, and other recommendations issuers to include detailed data release as a main request from the MFIs.