The role of credit officers in the performance of microcredit loans: evidence from Vivacred in Brazil

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Abstract

This paper studies the impact of credit officers on the performance of microcredit loans. We estimate a structural model of credit provision with costly verification state in which the ability of the credit officer is considered explicitly, using data from Vivacred - a Brazilian NGO. Our results suggest that (i) there is substantial heterogeneity among credit officers in the sample; (ii) the ability of credit officers has a measurable effect on the loan success; and (iii) the ability is correlated with experience.

1 Introduction

Asymmetric information is an essential aspect of credit markets. There is a substantial literature on how different aspects of contracts can help in mitigating the consequences of this phenomenon: screening ([Stiglitz and Weiss, 1981], collateral [Bester and Hellwig, 1987]), dynamic incentives ([Morduch, 1999a],

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[Armendáriz de Aghion and Morduch, 2000]), group lending ([Stiglitz, 1990] [Banerjee et al., 1994] [Besley and Coate, 1995] [Ghatak, 1999]).

Here, we focus on the role of credit officers as a direct way of dealing with asymmetric information issues. Credit officers are responsible to collect information about potential solvency of credit applicants and to verify the ex-post state of nature as in [Townsend, 1979] and [Gale and Hellwig, 1985]. Our analysis is based on a model of credit performance in which credit officers are considered explicitly. The key parameters of the model are estimated with data from Vivacred, which is a Brazilian NGO created in 1996 to provide microcredit in *favelas* in Rio de Janeiro.

The empirical setting provided by the Vivacred data is quite favorable for the sake of this study. First, there is information about who is the credit officer in charge of each contract. There are both cross-section and time series variation in the sample to estimate the parameter of each officer. Second, all contracts in the sample are homogeneous - they are individual contracts with the same interest rate). Third, different from other studies reviewed by [Hermes and Lensink, 2007], we have a large sample of more than 31,000 contracts for a period of 11 years.

Our analysis starts with a model of lending with costly verification states, where the credit officer performance affects the selection and the enforcement of the contract. The ability of the credit officer affects both the probability of success of the project financed and also the outcome from the auditing process of those who declared failure. From this model, we derive the probability of the payment delay as a function of the size of the loan, the client income and the ability of the credit officer. We then specify functional forms for all random variables of the model and for the distribution of the measurement errors of some variables in order to estimate the structural parameters of the

model by maximum likelihood.

Our estimates suggest substantial variation in the ability of the credit officers of Vivacred. Our measure of ability varies from 0.22 to 0.98 in a scale which is related to the probability of detecting client's misreporting. Data suggest that the credit officer makes a difference not only at the enforcement process but at the selection stage as well. The probability of success of a credit contract is highly correlated with the officer estimated ability. In addition the subjective cost of lying has a reasonable estimated distribution considering the distributions of the loans size and clients income.

The estimated ability of credit officers is positively correlated with inner and previous experience, measured in terms of number of effective credit contracts attended and age at hiring. This evidence suggests the existence of learning or the importance of relationship as suggested in [Berger and Udell, 1995], [Petersen and Rajan, 1995] and [Carrasco and Pinho de Mello, 2006].

Based on the estimates, we use the model to simulate different situations to illustrate the impact of the ability of credit officers on the delay. The baseline probability of delay observed in the data is 13.49%. For example, if we remove the heterogeneity among credit officers, this rate changes to 13.07% if we consider every officer has the same ability of the median officer or to 18.72% if all abilities are equal to the average. Repeating this exercise for the whole range of ability estimated, the rate of delay could vary from 51.03% if every officer is equal to the worst one to 1.11% if everyone is like the best one.

The remaining of the paper is organized as follows. Section 2 and 3 provide a description of Vivacred and the data considered in this study. Section 4 presents the model and the estimation of the structural parameters. The relationship between the officers profile and their estimated efficiency is de-

picted in section 5. Section 6 presents the simulation exercises. Section 7 concludes.

2 Vivacred

Vivacred is a non profit microcredit institution operating in Rio de Janeiro slums (*favelas*). It aims at providing access to credit for tiny and small firms in Rio de Janeiro and in particular in the low income communities and neighborhoods. It focuses on urban micro-business (formal or informal) such as storekeepers, craftsmen, and small service providers.

Vivacred started in Rocinha (the biggest favela in Brazil) at the end of 1996. Five other branches were created since then: Rio das Pedras in 1998, Copacabana (now in Gloria) in 1999, Maré in 2000, Santa Cruz in 2002 and in the city of Macaé (Rio state) in 2004. Vivacred is mostly funded by the Brazilian Development Bank (BNDES).

There is very little variation in the contract terms. The typical contract has a fixed monthly interest rate of 3.9% and an additional registration fee between 3% and 5% depending of the duration. In 11 years (1997 to 2007), 41,000 credits were solicited by 15,400 potential clients and 32,000 credits were disbursed to attend 11,400 actual clients.

Credit officers comprise an important mean of reducing asymmetric information problems. They have two main tasks during the process: (i) collect information about applicant solvency and present it to the credit committee for approval, (ii) check the ex-post state of nature and enforce the contract in case of payment delay. To better understand which steps of the process are influenced by the officer, it is useful to explain, step by step, how the credit cycle works in Vivacred, as summarized in figure 1.

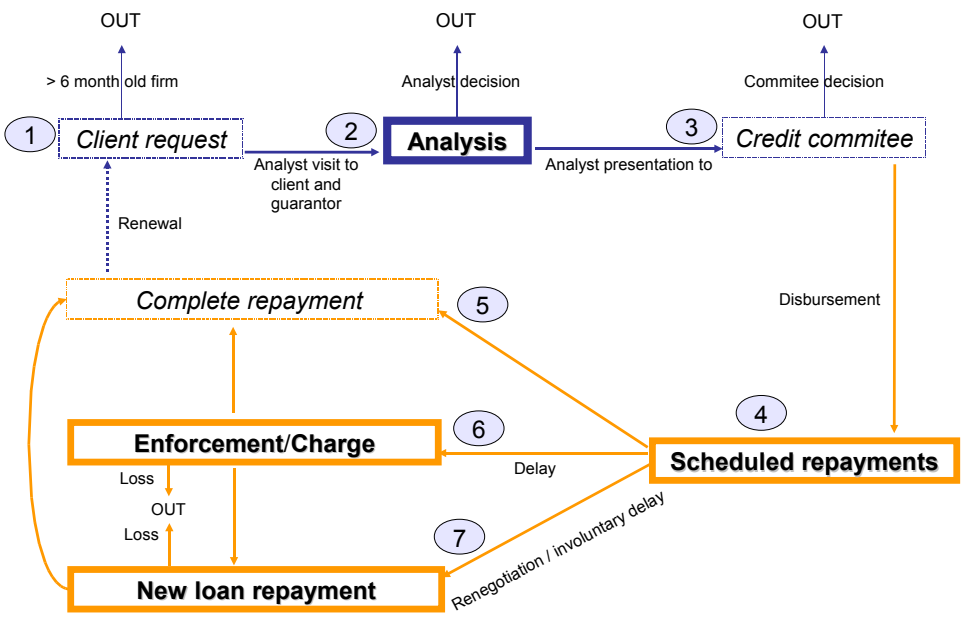


Figure 1: Credit cycle in Vivacred

The process starts with the client request (step 1). In order to be eligible, the borrower's firm cannot be created less than six month before the application and the client cannot be registered in the "Serviço de Proteção ao Crédito" - SPC[1]. To apply for a credit in Vivacred, the client has to present ID documents of both himself and the guarantor(s), along with the documents of the firm. In addition, the purpose of the loan has to be explained.

An important issue for the purpose of this study is how credit officers are assigned to each contract. There is no strategic consideration on the allocation of the credit officers according to the Vivacred executives. The match between clients and officers is made by geographic area, aiming at reducing operational costs.

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

The credit officer visit the client and the guarantor (step 2) for gathering the information on the collateral, solvency and business risk. The applicant is met at the business location. The client is asked to fill a questionnaire about his personal situation, the household budget and the financial situation of the firm (for more details see the data set description in section 3). The same questions are asked to the guarantor, although the financial information is not as detailed.

This process of data collection is particularly demanding for the analysts. The typical client does not use to hold formal accountability; neither for the business nor for the household budget. Thus, in order to evaluate the business balance sheet and the household budget, the credit officer makes indirect questions. Social skills, experience and prior knowledge of other business in favelas are very important to obtain reliable information about the business at this point. For example, the officer ask questions about the monthly and weekly amounts spent and received in different roundabout ways to check the coherence of declared values. Or the officer might ask for rough evaluations of stock and main items of the budget. After completing the basic information set, the officer helps the client to parameterize the proposal, establishing the size of the loan and the number of installments.

This application is then presented to the credit committee (step 3). The committee has the final word on the approval and the terms of the loan, which might differ from the initial proposal. In case of approval, the client receives the money and begins repayments in the following month (step 4). Installments can be paid on a monthly or semi-monthly basis, in cash or check. Sometimes the officer can even collect the money direct from the client.

In case of repayment (step 5), which means paying the whole value without significant delays, the client typically get access to another loan, possibly of

bigger value. If there are no delay during the whole period of the contract, the registration fee (TAC) of the subsequent loan is reduced.

In case of delay (step 6), officers play another important role on the process. It starts with the respective officer visiting the client and trying to convince him/her to pay the installment. At the beginning of every workday, each credit officer receives a list of delayed contracts. In one or two days of delay, credit officers start to call clients. At this stage, the officers not only negotiate with the client but also help in finding ways of paying the debt. For example, a new loan repayment can be offered (step 7) if the client shows his good-faith. Credit officers put most of the effort to get the repayment within a delay period of 30 days which, along with credit origination, determines the variable portion of their monthly wage compensation. After 180 days of delay, the loan is considered lost. In case of default, the client is included on the SPC in case of negotiation failure.

3 Data description

We have data on all credit contracts of Vivacred in the period of 1997 to 2007, from all the six branches. This sample consists on about 32,000 actual contracts. Our sample comprises all the relevant dimensions of the credit contract - the client, the credit officer and the guarantor, the contract and the business characteristics. All the financial variables are deflated to January 1997, according to the consumer price index (IPC) for the city of Rio de Janeiro.

We restrict our sample to approved contracts - only the actual (disbursed) contracts are considered. We have removed from our data the 79 contracts without credit officer identification, the 146 contracts made by 6 trainee officers, the 113 contracts in group and the 25 contracts with null income.

Contracts defined as "special loans", designed mainly to employees, were also removed because they fell outside of Vivacred's main activity.

The standard loan is individual (as opposed to group loans), restricted for firms with more than six months since creation. The duration varies according to the use of the money, being typically one year for capital expenditures or two years for capital investments. In addition, there are short-term contracts, with less than 4 months, discount of receivables (mainly checks), and others. We have excluded joint liability group loans because they are about only 1% of our sample and are associated with different incentive mechanisms.

Each contract is classified as "paid", "delayed", or "defaulted". We create dummy variables indicating delay with more than 7, 15 and 30 days. A delay above 180 days is considered default - a situation in which the outstanding debt is considered lost, although being recoverable afterwards. We focus on the 30 days delay variable, since it is one of the targets of the credit officer compensation wage.

Descriptive statistics of the delay variables are summarized in the table 1. The proportion of loans with at least one delayed repayment is respectively 13.4%, 11.2% and 8.6% considering the 7, 15 and 30 days thresholds. Moreover, 3.4% of the loans are (at least partially) in default (delay above 180 days), representing 2.7% of the lended amount.

Table 1: Summary statistics

N = 31,692	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Delay 7 days	0.134	0.341	0	1
Delay 15 days	0.112	0.315	0	1
Delay 30 days	0.086	0.280	0	1
Delay 180	0.034	0.181	0	1

Table 2 presents descriptive statistics on the main variables available in our sample, grouped according to alternative definitions of delay.

Over the 11 years of the Vivacred experience, the average approved loan is R$ 1,014, with 9 installments, for which 93% were signed jointly with a guarantor and 32% were financing capital investment. Delayed contracts are smaller (especially considering delays over 180 days) and have a higher number of installments. Half of the contracts were made for the services sector and 29% for small retailers.

Vivacred clients are well balance in terms of demographic profile: gender, marital status, taking care of dependents or not. Different from other MFI, there is no pro-women policies. However, the proportion of men is higher for credits with higher delay. Clients with late payment above 180 days are less likely to be married (35% against 50%) or to take care of dependents (28% against 22%). They are also 4 years younger.

The household extra income, household consumption and business profits are, respectively, R$292; R$525 and R$940, on average. The average available income of the guarantor (income-consumption) is R$483. The client extra income and the guarantor available income are substantially lower for delayed contracts - as measured in terms of 30 or 180 days. For the case of client consumption and business profit, the same occurs only for the 180 delay.

In addition delayed credits are associated with a higher proportion of loan repayment, which represents the renegotiation process after delay; and a shorter relationship, measured in terms of number of credits (requested or approved) as well as in number of months.

Table 2: Descriptive statistics by delay thresholds

Delay	**All credits**	**30 days**			**180 days**		
		$<$	$\geq$	Dif.	$<$	$\geq$	Dif.
Obs	31692	28964	2728		30606	1086	
				Credit characteristics			
Credit value	1014.2	1052.6	1030.0	22.54	1061.9	732.9	329.0***
Installments	9.04	9.17	9.47	-0.301***	9.17	9.85	-0.677***
Guarantor	0.931	0.929	0.953	-0.0247***	0.931	0.935	-0.0038
K investment	0.320	0.325	0.340	-0.0155	0.328	0.279	0.0492**
Loan repayment	0.095	0.090	0.126	-0.0359***	0.090	0.196	-0.106***
				Client characteristics			
Men	0.504	0.502	0.552	-0.0498***	0.505	0.540	-0.0341*
Married	0.476	0.503	0.373	0.129***	0.496	0.362	0.134***
Have dependents	0.522	0.527	0.504	0.0232*	0.529	0.414	0.115***
Age	42.4	42.4	39.2	3.2***	42.3	38.4	3.9***
Extra Income	291.6	299.3	227.6	71.70***	297.8	156.4	141.5***
Consumption	525.1	525.7	577.1	-51.45***	533.8	427.9	105.9***
				Guarantor characteristics (when required)			
Men	0.577	0.577	0.579	-0.00240	0.577	0.584	-0.00745
Married	0.417	0.426	0.323	0.103***	0.420	0.309	0.111***
Age	46.4	46.39	46.06	0.339	46.48	43.16	3.315***
Income-consumption	483.4	549.8	204.2	345.6***	526.3	323.8	202.6***
				Relationship (months and number of previous credits)			
Active (months)	17.3	17.58	8.435	9.149***	17.01	10.38	6.629***
Total (months)	19.96	20.26	9.294	10.97***	19.56	11.76	7.804***
# credits	2.31	2.30	1.12	1.182***	2.23	1.25	0.988***
# demands	2.61	2.61	1.36	1.254***	2.53	1.50	1.034***
				Business characteristics			
Profit	940.4	953.2	988.2	-34.99	959.1	876.5	82.57*
Agriculture	0.0328	0.0337	0.0251	0.00861*	0.0330	0.0306	0.00241
Services	0.5001	0.509	0.427	0.0815***	0.499	0.557	-0.0578***
Retail trade	0.293	0.291	0.228	0.0626***	0.284	0.326	-0.0422**
Other sectors	0.174	0.167	0.319	-0.153***	0.184	0.0860	0.0976***

Data about the credit officers were collected directly from the Vivacred files. We have data on: age, gender, education, marital status, address, wage, hiring and layoff (if applicable) dates, experience (years since first job), previous positions (administrative, financial or sales experience). Table 3 depicts descriptive statistics on officers attributes.

Table 3: Summary statistics : Credit officers profile

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Men	0.475	0.505	0	1	40
Married	0.45	0.503	0	1	40
Have children	0.5	0.506	0	1	40
Living in favela	0.5	0.506	0	1	40
College	0.6	0.496	0	1	40
Exp. before Vivacred	7.638	5.751	0.5	27	36
Exp. in finance	0.472	0.506	0	1	36
Exp. in sales	0.583	0.5	0	1	36
Age at entrance	28.773	7.284	19.463	60.558	40
Age at exit	32.438	7.415	20.282	61.808	40
Adm. tasks before	0.125	0.334	0	1	40
Max. wage	936.762	368.055	450	2037.430	40
# months in Vivacred	44.591	33.339	1.600	130.899	40
# credits disbursed	792.537	805.673	28.523	3768.179	40

The set of officers is well balanced in the demographic dimensions: 47.5% are men, 45% are married, one half has children and one half lives in a favela. Their educational level is quite high for Brazilian terms - 60% have college. They had, on average, 7.6 years of experience before being hired by Vivacred, having 47% with previous occupation requiring financial skills and 58% with previous experience in sales. Information about professional experience previous Vivacred is missing for 4 officers. Moreover, the typical officer got in Vivacred at almost 29 years old, stays 45 months taking care of 793 actual credits (excluding not approved credits). He/she was hired to accomplish administrative tasks before to be an officer in 12.5% of the cases. The fixed

part of his salary at the exit (or present one) is R$ 937.

Table 4 presents the relationship between residence and education of credit officers, showing that college level education is less frequent among those living in favelas. At the beginning of Vivacred, the typical profile involved profile with college and living out of favelas. The recent trend is inverted.

Table 4: Education X Residence

# officers	Out of favela	In favela	Total
Without college	3	13	16
With college	17	7	24
Total	20	20	40

Finally, there is one caveat regarding the data collecting process in Vivacred. First-time borrowers have more reliable data and a more complete information set. This is because there is only an update of the relevant issues in the subsequent contracts, when the borrower behaves well. As a consequence, the occurrence of missing information increases with the number of contracts each borrower sign. For this reason, we impute some missing variables considering the observed average of previous contracts.

4 The effect of credit officers ability on the performance of the loans

4.1 Model

This model is widely inspired by the Vivacred practice, where the ability of credit officers affects both the selection and the state verification steps of the credit process. The model is used to provide the probability of a payment delay as a function of the loan size, the client income and the credit officer

ability parameter.

We consider the relationship between a lender and a borrower. We assume the borrower has a project that requires a fix investment of size L, which can be financed at the (gross) interest rate $\rho > 1$. The return of the project is a binary random variable with values $r \in \{\underline{r}, \overline{r}\}$, where $\Pr(r = \overline{r}) = p$ and $\overline{r} > \rho > \underline{r}$. The true state of the nature is not observed by the lender.

The return of the project is observed only by the borrower, which reports a return $\hat{r}$ in the end of the contract. An announcement of $\hat{r} = \underline{r}$ is made through the delay of payment, which is interpreted as the first signal that the borrower is not able to repay the loan. In this case, the lender send the credit officer to visit the borrower and audit the true state of the nature. The quality of the audit process depends on the credit officer ability α which is the probability of learning the true state of the nature. A borrower who is found misreporting the true state has to repay the total amount ρL plus additional costs $\tau L + \phi$, where τL represents a penalty that varies with the loan size and ϕ is interpreted as the value of reputation for the borrower.

If $r = \underline{r}$ or if the audit process fails, the borrower pays with all the presumed available resources $\min(\underline{r}L + I, \rho L)$, where I is the additional resources put as collateral in the credit contract. Typically, I comes from other income sources of the borrower or from the business. The guarantor income is implicitly included in ϕ and does not have to be incorporate to I.

The borrower payoffs in each situation are summarized in the following table:

state of nature	announcement	audit	cost
$r = \overline{r}$	$\hat{r} = \overline{r}$	none	ρL
$r = \overline{r}$	$\hat{r} = \underline{r}$	success	$(\rho + \tau)L + \phi$
$r = \overline{r}$	$\hat{r} = \underline{r}$	fail	$\min(\underline{r}L + I, \rho L)$
$r = \underline{r}$	$\hat{r} = \overline{r}$	none	ρL
$r = \underline{r}$	$\hat{r} = \underline{r}$	success	$\min(\underline{r}L + I, \rho L)$
$r = \underline{r}$	$\hat{r} = \underline{r}$	fail	$\min(\underline{r}L + I, \rho L)$

The borrower always report the true state of the nature when the project fails, paying $\min(\underline{r}L + I, \rho L)$. There is no incentive to misreport in this case. If the project is successful, on the other hand, there is a wrong announcement only if:

$$\alpha\left[(\rho + \tau)L + \phi\right] + (1 - \alpha)\min(\underline{r}L + I, \rho L) < \rho L,$$

which can be written as

$$\begin{aligned} \phi &< \frac{1}{\alpha}\left[(\rho - \underline{r} - \alpha(\rho - \underline{r} + \tau))L - (1 - \alpha)\min(I, (\rho - \underline{r})L)\right] \\ &\equiv g(L, \rho, \underline{r}, \alpha, \tau, I). \end{aligned} \tag{1}$$

If the distribution of the reputational cost ϕ can be represented by F, we have that

$$\Pr(\hat{r} = \underline{r} | r = \overline{r}) = F(g(L, \rho, \underline{r}, \alpha, \tau, I)). \tag{2}$$

There is delay in two situations - in case of project failure or in case of a misreport about the success of the project. If we denote the define D as a binary variable indicating delay, we have

$$\Pr(D = 1) = 1 - p(\alpha) + p(\alpha)\Pr(\hat{r} = \underline{r} | r = \overline{r})$$

and, substituting (2),

$$\Pr(D = 1) = 1 - p(\alpha) + p(\alpha)F(g(L, \rho, \underline{r}, \alpha, \tau, I)). \tag{3}$$

Thus, the ability of the credit officer α affects the performance of the credit contracts through two channels. First, better officers select better projects, with lower chance of failure. Second, borrowers are less willing to misreport when dealing with better officers because they anticipate a higher chance of punishment.

Notice that the model assumes there is no strategic allocation between credit officers and clients. We rule out, for instance, the possibility of having an officer with higher α (more efficient) assigned to a client with smaller ϕ (more likely to lie). The motivation behind this structure comes from the prevailing rule in Vivacred. The allocation of credit officers in Vivacred is primarily determined by the location of the business or the client home.

4.2 Estimation

Let's assume that we have a sample of N credit loans, indexed by $i = 1, ..., N$, with data on delay D_i, size of the loan L_i and the income used as collateral I_i . For each credit loan i, we also observe the identity of the credit officers, who are indexed by $j = 1, ..., M$. We denote by $j(i)$ the identity of the officer j who is assigned to client i. The interest rate and penalty are known and do not vary among borrowers ($\rho = 1,4$ and $\tau = 0.2$). The reputational cost ϕ is drawn from a log-normal distribution with parameters k_1 and k_2.

We can obtain the likelihood function from equation (3):

$$\mathcal{L}(\{\alpha_j\}_{j=1}^{M}, p(\cdot), \underline{r}, k_1, k_2 | \mathbf{D}, \mathbf{L}, \mathbf{I}, \rho, \tau) = \prod_{i=1}^{N} [1 - p(\alpha_{j(i)})(1 - F(g(L_i, \rho, \underline{r}, \alpha_{j(i)}, \tau, I_i)))]^{D_i=1} \times \times [p(\alpha_{j(i)})(1 - F(g(L_i, \rho, \underline{r}, \alpha_{j(i)}, \tau, I_i)))]^{D_i=0} \quad (4)$$

where $p(\cdot)$ is a function $p : [0,1] \rightarrow [0,1]$ to be specified. We consider a functional form for $p(\cdot)$ which allows the ability of the credit officer at the selection stage to be positively or negatively related to the ability of detecting the true state of the nature. We take $p(\alpha)$ as a linear function of α with the restriction of having values in the interval $[0,1]$. Thus,

$$p(\alpha) = \begin{cases} 0, & \text{if } \alpha < -\frac{\bar{p}}{\mu}; \\ \mu\alpha + \bar{p}, & \text{if } -\frac{\bar{p}}{\mu} \leq \alpha \leq \frac{1-\bar{p}}{\mu}; \\ 1, & \text{if } \alpha > \frac{1-\bar{p}}{\mu}. \end{cases} \tag{5}$$

There are two other issues to take into account. First, $\underline{r}$ is not observed for us (although it is for the client) and can vary from one client to the other. Then, we consider $\underline{r} \in \{\underline{r}_1, ..., \underline{r}_K\}$ ($\underline{r} < \rho$) with probability of $1/K$ in each possibility and integrate the parameter out of the likelihood function.

Second, although we have data on monthly extra income (E_I) and business profit (B_P), we don't know how much can be obtained by the lender in case of default. We define the income "available" as a proportion of the monthly extra income and of the business profit, both multiplied by the number of months planned to the repayment (m). The proportion of these two sources of income are not necessarily the same. $I = (\beta_{EI} * E_I + \beta_{BP} * B_P) * m$. We estimate these two coefficients in the likelihood maximization.

Substituting (5) into (4) and considering the distributions of $\underline{r}$ and I, the estimation problem is given by:

$$\max E_{\underline{r}} \mathcal{L}(\{\alpha_j\}_{j=1}^{M}, \mu, \bar{p}, k_1, k_2, \beta_{EI}, \beta_{BP}, \underline{r} | \mathbf{D}, \mathbf{L}, \mathbf{EI}, \mathbf{BP}, \rho, \tau) \tag{6}$$

subject to

$$0 \leq \alpha_j \leq 1$$

$$0 \leq \mu \cdot \alpha_j + \bar{p} \leq 1$$

$$0 \leq \beta_{EI} \leq 1$$

$$0 \leq \beta_{BP} \leq 1$$

5 Empirical results

5.1 Parameter estimates

Tables 5 presents the estimated parameters related to the probability of success (μ , $\bar{p}$), the ϕ distribution parameters (k_1, k_2), the parameters defining the "available" income (β_{EI}, β_{BP}) and some summary statistics about the estimated α's and $p(\alpha)$'s.

Table 5: Maximum likelihood estimates

Estimated α 's					
α_1	0,773	(0,0003)	α_{21}	0,872	(0,0005)
α_2	0,562	(0,0301)	α_{22}	0,819	(0,0001)
α_3	0,357	(0,0302)	α_{23}	0,771	(0,0003)
α_4	0,631	(0,0084)	α_{24}	0,882	(0,0004)
α_5	0,800	(0,0007)	α_{25}	0,749	(0,0020)
α_6	0,824	(0,0003)	α_{26}	0,811	(0,0149)
α_7	0,654	(0,0042)	α_{27}	0,571	(0,0048)
α_8	0,606	(0,0041)	α_{28}	0,861	(0,0000)
α_9	0,847	(0,0003)	α_{29}	0,016	(0,0445)
α_{10}	0,596	(0,0047)	α_{30}	0,929	(0,0006)
α_{11}	0,335	(0,0164)	α_{31}	0,499	(0,0080)
α_{12}	0,834	(0,0016)	α_{32}	0,767	(0,0016)
α_{13}	0,801	(0,0006)	α_{33}	0,803	(0,0015)
α_{14}	0,800	(0,0003)	α_{34}	0,819	(0,0009)
α_{15}	0,811	(0,0005)	α_{35}	0,569	(0,0061)
α_{16}	0,286	(0,0613)	α_{36}	0,802	(0,0012)
α_{17}	0,541	(0,0083)	α_{37}	0,896	(0,0008)
α_{18}	0,251	(0,0269)	α_{38}	0,778	(0,0010)
α_{19}	0,816	(0,0005)	α_{39}	0,813	(0,0003)
α_{20}	0,814	(0,0003)	α_{40}	0,753	(0,0008)
Summary statistics					
	α's	**$p(\alpha)$'s**		**α's**	**$p(\alpha)$'s**
Mean	0,693	0,901	Median	0,789	0,940
Minimum	0,016	0,625	Maximum	0,929	0,997
Other parameters					
μ	0,407	(0,00852)	$\bar{p}$	0,619	(0,00606)
k_1	120,31	(79030,3)	k_2	95,15	(52914,1)
β_{EI}	0,914	(0,04643)	β_{BP}	0,006	(0,00002)

Note: standard errors in parenthesis.

The average α is 69.3%, ranging from a minimum of 1.6% to the maximum of 99.7%. The estimated values of μ and $\bar{p}$ as 0.407 and 0.619, respectively, determine also important variation in the $p(\alpha)$'s. Figure 2 presents the estimated α's and $p(\alpha)$'s, ranked from the lower to the higher. Credit officers matter for the two stages of the credit process - selection and audit stages. Moreover, these two dimensions are positively correlated.

Figure 2: Estimated α's and $p(\alpha)$'s

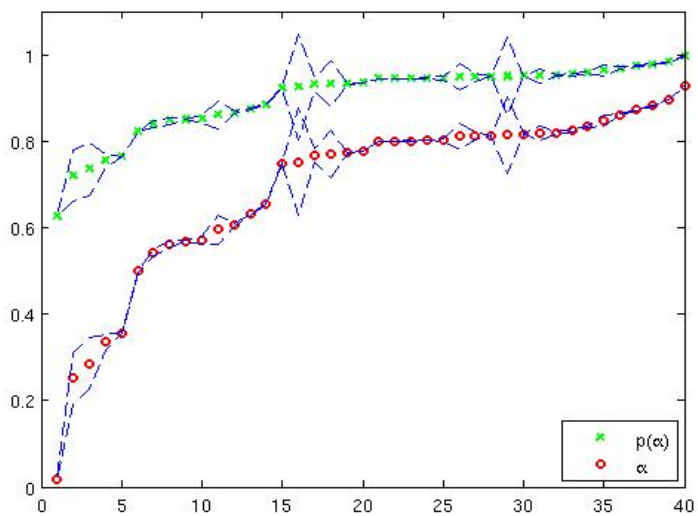
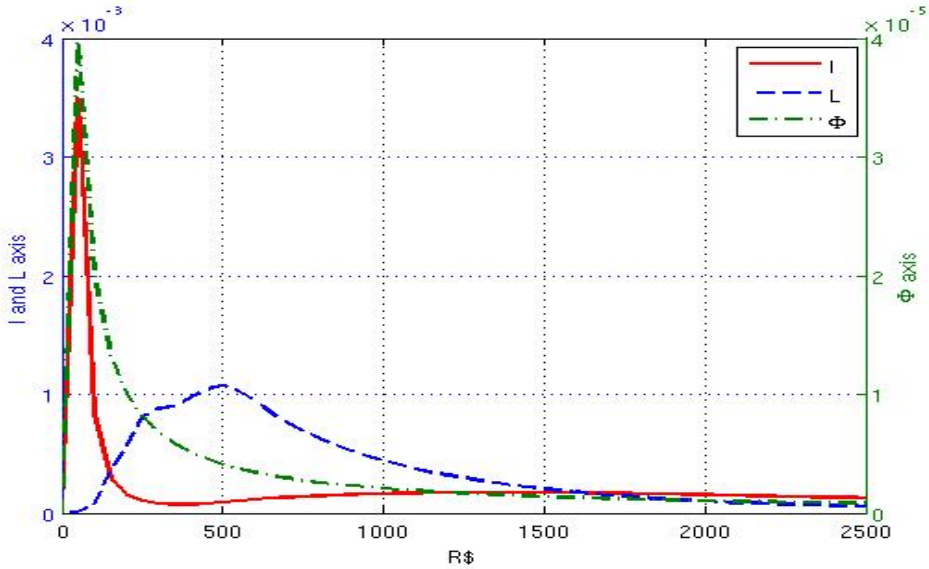


Figure 3 depicts the the estimated distribution of the reputational cost ϕ, comparing it with the empirical distributions of the "available" income I and the loan size L. The estimation of the parameters k_1 and k_2 needs some clarification. A deeper inspection of the likelihood reveals that the distribution of ϕ matters only through the fraction of individuals with incentive to misreport, i.e., with $\phi < g(L, \rho, \underline{r}, \alpha, \tau, I)$. Parameters k_1 and k_2 are not completely identified.

Figure 3: Income, debt and reputational cost



To better understand the meaning of this result, we now decompose the probability of delay in two components - failure and misreporting. The decomposition comes from equation (3). For each contract, we use the estimated parameters to compute averages. The average predicted probability of delay is 8,65%, the average estimated probability of success $p(\alpha)$ is 93,27%, and the probability of misreporting is 2,07%. Thus, 22,27% of the probability of delay is explained by misreporting (0.9327*0.0207/0.0865=0.2227). This illustrates the importance of officers expertise in auditing. The prediction of the model is quite good as 8,61% of the credits have a delay above 30 days.

5.2 Credit officer's profile

Given α, the measure of ability of the credit officers estimated on the previous section, we analyze here how this measure is correlated with observed characteristics of credit officers. Table 6 presents the regressions of the α's on observed characteristics of the credit officers.

Table 6: OLS Regression: α on credit officers profile

	(1)	(2)	(3)	(4)	(5)	(6)
Men	-0.0546	-0.0713	-0.0422	-0.0280	-0.0463	-0.0663
	(0.0632)	(0.0670)	(0.0737)	(0.0675)	(0.0643)	(0.0630)
Married	0.0985	0.0807	0.102	0.0549	0.0610	0.0512
	(0.0704)	(0.0671)	(0.0803)	(0.0699)	(0.0666)	(0.0644)
Have children	0.0824	0.0265	0.0126	0.0939	0.0624	0.0215
	(0.0723)	(0.0731)	(0.0876)	(0.0714)	(0.0674)	(0.0687)
Favela resident	0.0614	0.0168	0.0406	-0.0440	-0.00776	0.0144
	(0.0743)	(0.0827)	(0.0974)	(0.0853)	(0.0797)	(0.0778)
Superior grade	-0.0275	-0.111	-0.0633	-0.140	-0.0988	-0.0955
	(0.0761)	(0.0837)	(0.0998)	(0.0851)	(0.0819)	(0.0790)
Adm. tasks before		0.0401	0.0381	-0.0705	-0.0387	0.0234
		(0.107)	(0.115)	(0.105)	(0.0981)	(0.100)
Max. wage (log)		0.219**	0.189	0.0240	0.0259	0.0265
		(0.104)	(0.112)	(0.154)	(0.135)	(0.130)
Age at entrance		0.00774				0.00841*
		(0.00489)				(0.00460)
Years of exp.			0.00832			
			(0.00679)			
Months in VC				0.00281		
				(0.00173)		
# credits (log)					0.0730**	0.0771**
					(0.0353)	(0.0342)
Constant	0.619***	-0.975	-0.678	0.462	0.103	-0.155
	(0.0870)	(0.688)	(0.706)	(0.975)	(0.755)	(0.742)
Observations	40	40	36	40	40	40
R^2	0.223	0.362	0.354	0.365	0.394	0.455

Standard errors in parentheses

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

Gender, marital status, residence (in or out favela) and education are not related to the estimated ability. To take in account the previous and inner experience of the credit officer, we introduce successively several measure. To take in account the experience acquired before to be hired by Vivacred, we can use alternatively the number of year of professional experience and the age at which the officer was hired. To take in account the experience in Vivacred we can use alternatively the number of month worked for Vivacred or the number of contracts attended. This last measure of experience appears as the only trait that matters for ability.

This result may reflect a pure selection effect, in which only the most productive officers remain working in Vivacred. But it may also suggest that the job of the credit officers is subject to a learning-by-doing process. Unfortunately, we do not have the means of differentiating among the two potential effects.

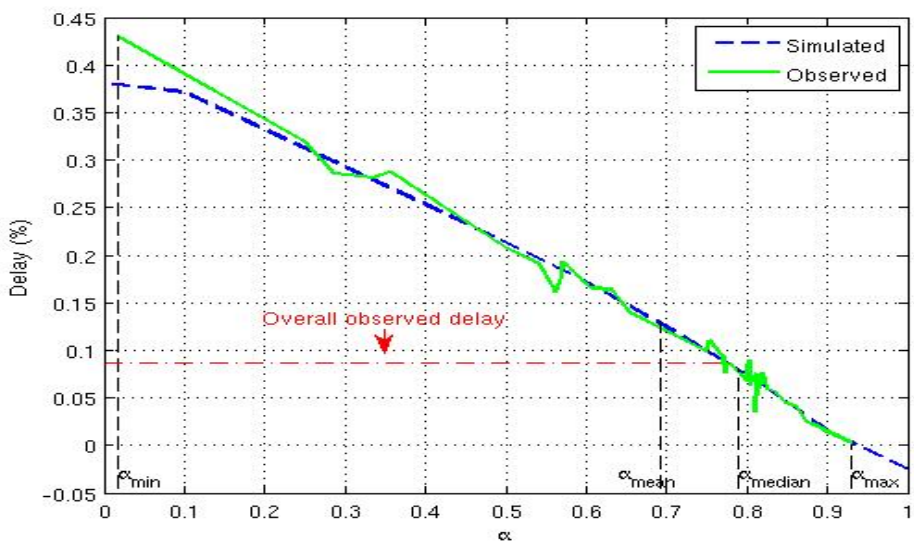
Wages are significant in table 6 only when experience is not included as independent variables. However, it is important to notice here that our data contain only information about the recurrent fixed-wage. Part of the earnings of the officers consists in bonuses that we do not observe in our data.

5.3 Simulations: Eliminating heterogeneity

The overall observed delay above 30 days represent 8.61% of our sample. We use simulations to estimate what would be the delay if all Vivacred credit officers had the same ability parameter α, considering different values of α in the $(0, 1)$ interval. Then, we are able to compare this simulated proportions of delay to the actual proportion of credits with delay above 30 days for each level of α (each credit officer).

Figure 4 summarizes the results of the simulations and overlay the observed delay. The horizontal axis represents the α considered in each simulation exercise, while the vertical axis depicts the simulated and observed delay. The proportion of credits with a delay above 30 days is highly affected by the ability of the credit officers. Considering the range of abilities estimated with our data, simulated delay vary from 0,1% to 38% while the observed delay vary from 0,3% to 43%.

Figure 4: Simulated and observed delay by homogeneous α



Thanks to the model, it also possible to simulate the effect of interventions that potentially affect the average ability of the credit officer team. For example, an increase in 10% on the ability of the officers of Vivacred would reduce the expected delay of credit loans from 8,61% to 4,44% (a reduction of 10% would increase the delay to 12,64%).

6 Conclusion

This paper focuses on the role of the credit officer as an important means of dealing with asymmetric information. We show that the credit officer performance significantly affect both the selection and the enforcement stages of the contract. Furthermore, our estimated ability varies a lot from one officer to another and this variation is related to the officer experience.

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Appendix 1: a validation exercise

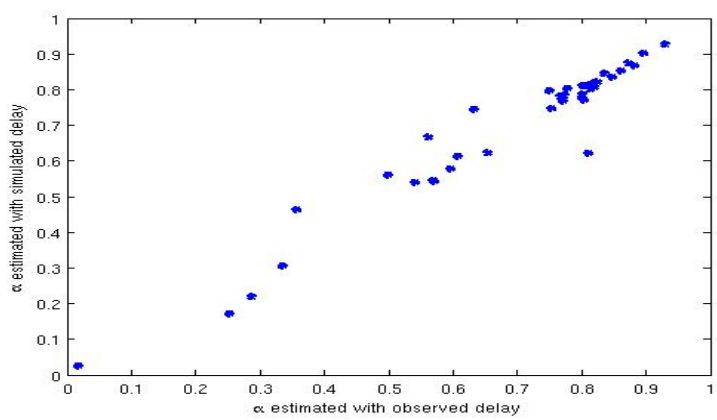
In order to check the validity of our estimation procedure, we generate data from the model and try to recover the true parameters using our method. We simulated a dummy of delay based on the estimated parameters and the observations of "available" income I and the loan value L.

Table 7: Estimated parameters

Other parameters		**Summary**	α**'s**	$p(\alpha)$**'s**
μ	0,406	Mean	0,6914	0,9019
$\bar{p}$	0,621	Median	0,7824	0,9388
k_1	116,38	Weighted mean	0,6450	0,8831
k_2	100,56	Minimum	0,0254	0,6314
β_{EI}	0,894	Maximum	0,9275	0,9978
β_{BP}	0,012	function value	8726,66	

We then estimate the parameters of the model using this simulated dummy of delay. The estimated set of parameters is presented in table 7 and figure 5. The procedure is able to recover the true value of the parameters properly.

Figure 5: α's estimated with observed and simulated delay



Appendix 2: Computing the gradient

The problem to be solved is:

$$\max_{\{\alpha_j\}_{j=1}^M, \mu, \bar{p}, k_1, k_2} E_\varepsilon E_{\underline{r}} \mathcal{L}(\{\alpha_j\}_{j=1}^M, \mu, \bar{p}, \underline{r}, k_1, k_2 | \mathbf{D}, \mathbf{L}, \tilde{\mathbf{I}} + \varepsilon, \rho, \tau)$$

subject to

$$0 \leq \alpha_j \leq 1$$

$$0 \leq \mu \cdot \alpha_j + \bar{p} \leq 1$$

Tacking the log-likelihood function as:

$$Log\mathcal{L}(\{\alpha_j\}_{j=1}^M, \mu, \bar{p}, k_1, k_2 | \mathbf{D}, \mathbf{L}, \mathbf{I}, \rho, \tau) = \sum_{i=1}^N log(Pr(D=1)) \cdot 1_{D_i=1} + log(Pr(D=0)) \cdot 1_{D_i=0}$$

with $Pr(D=1) = 1 - (\mu\alpha_{j(i)} + \bar{p})(1 - F(g(L_i, \rho, \underline{r}, \alpha_{j(i)}, \tau, I_i)))$

and $g(L, \rho, \underline{r}, \alpha, \tau, I) \equiv \frac{(\rho - \underline{r} - \alpha(\rho - \underline{r} + \tau))L - (1-\alpha)\min(I, (\rho - \underline{r})L)}{\alpha}$

and ϕ has a lognormal distribution:

$$F(x, k_1, k_2) := \int^x \frac{\mathrm{e}^{-1/2 \frac{(\ln(u) - k_1)^2}{{k_2}^2}}}{u \cdot k_2 \sqrt{2 \cdot \pi}} du; f(x, k_1, k_2) = \frac{\mathrm{e}^{-1/2 \frac{(\ln(x) - k_1)^2}{{k_2}^2}}}{x \cdot k_2 \sqrt{2 \cdot \pi}}$$

The partial derivative of the log-likelihood function in $\theta \in \{k_1, k_2, \{\alpha_j\}_{j=1}^M, \mu, \bar{p}\}$ is:

$$\frac{dLog\mathcal{L}}{d\theta} = 1_{D_i=1} \cdot \frac{\frac{dPr(D=1)}{d\theta}}{Pr(D=1)} - 1_{D_i=0} \cdot \frac{\frac{dPr(D=1)}{d\theta}}{1 - Pr(D=1)}$$

Partial derivatives in μ and $\bar{p}$

The partial derivatives of the probability of delay in the probability of success parameters (μ and $\bar{p}$) are:

$$\frac{dPr(D=1)}{d\mu} = -\alpha_j \cdot (1 - E_\varepsilon E_{\underline{r}} F(g(L_i, \rho, \underline{r}, \alpha_{j(i)}, \tau, I_i), k_1, k_2))$$

and

$$\frac{dPr(D=1)}{d\bar{p}} = -(1 - E_\varepsilon E_{\underline{r}} F(g(L_i, \rho, \underline{r}, \alpha_{j(i)}, \tau, I_i), k_1, k_2))$$

Partial derivative in k_1 and k_2

The partial derivatives of the probability of delay in the normal distribution parameters (k_1 and k_2) are:

$$\frac{dPr(D=1)}{dk_1} = (\mu \cdot \alpha + \bar{p}) \cdot E_\varepsilon E_{\underline{r}}[-\frac{\mathrm{e}^{-1/2\,\frac{(\ln(g(.))-k_1)^2}{{k_2}^2}}}{k_2\sqrt{2\cdot\pi}}]$$

and

$$\frac{dPr(D=1)}{dk_2} = (\mu \cdot \alpha + \bar{p}) \cdot E_\varepsilon E_{\underline{r}}[\frac{\mathrm{e}^{-1/2\,\frac{(\ln(g(.))-k_1)^2}{k_2^2}}}{k_2\sqrt{2\cdot\pi}} \cdot (\ln(g(.)) - k_1)]$$

Partial derivative in $\alpha_1, \ldots, \alpha_M$

The partial derivatives of the probability of delay in the officers ability coefficient ($\alpha_1, \ldots, \alpha_M$) are:

$$\frac{dPr(D=1)}{d\alpha_j} = E_\varepsilon E_{\underline{r}}[f(g(.), k_1, k_2) \cdot \frac{dg(.)}{d\alpha_j}] - \mu \cdot (1 - E_\varepsilon E_{\underline{r}} F(g(.), k_1, k_2))$$

with

$$\frac{dg(L, \rho, \underline{r}, \alpha_j, \tau, I)}{d\alpha_j} = \begin{cases} 0 & \text{if } I \geq L(\rho - \underline{r}) \\ \frac{I - L\cdot(\rho - \underline{r})}{\alpha_j^2} & \text{if } I < L(\rho - \underline{r}) \end{cases}$$