The looking-glass self effect on the microcredit market: theory and evidence from a French MFI

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Abstract

In this paper we analyze how decisions of a micro-finance institution (MFI) can impact borrowers' behavior. We first model a situation where the MFI – through a follow-up process – and the agent can act on the probability of the borrower's project to succeed. We show that, whereas (i) under symmetric information, the MFI optimally helps more the borrower with lower probability of success, (ii) this may not be the case under asymmetric information, when the MFI has better information on success probability than the borrower (what is likely to be the case on micro-credit market). In this last case, because of a "looking-glass self" effect, a high level of help can undermine borrower's belief about his type. Under realistic assumptions, the optimal choice of help is first increasing and then decreasing with the probability of success. We then test this prediction using data from a French MFI. We build trivariate (probit and mixed) models to test empirically how training programs are assigned to different types of borrowers. Confirming our theoretical reasoning, we find a non-monotonic relationship between the MFI's decision to follow-up and the risk of micro-borrowers. The probability to be followed-up appears to increase with risk for low-risk agents and to decrease for high-risk agents.

Key Words: microcredit, reversed asymmetric information, looking-glass self, trivariate probit and mixed models

JEL Classification: C34, C41, D82, G21

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1 Introduction

Microcredit is a small-scale financial tool designed for individuals who are rejected from the classical financial market. After having been widely used and studied in developing countries, microcredit is now highly spreading to developed countries. While its main objective - poverty alienation - is common for both types of economies, its implementation has several particularities in the developed countries. For example, individual lending is prevalent (instead of group lending in developing countries), loans don't specifically target women and there is often a high government implication through guaranties or subsidies in richer economies. Another important characteristic of microfinance in the developed countries is the presence of a well-defined borrowers' follow-up strategy. The follow-up (or help, more generally) mainly consists of training programs created to support microborrowers to start-up or develop a business. In contrast, in developing countries training programs take mainly the form of social development programs (information on health, civil responsibilities and rights, rules and regulations of the bank, etc.). This non-financial support is sometimes included in the contract offered by the MFI to the borrower. According to annual report published by l'Observatoire de la Microfinance Banque de France in 2010, the follow-up is a salient characteristic of French microfinance.

Microborrowers are usually unemployed people without collateral, who need financing for their project. There is an important aspect that generally characterize these borrowers. Microborrowers generally lack experience. They often need financing to start-up a business for the first time in their life. Therefore, they lack entrepreneurial, managerial experience or means to evaluate the market. Thus, the microfinance institution might be better informed then the borrower about the potential success of the project. The MFI might explore this superiority of information while deciding on the contract to offer. In this paper we will focus on this significant feature of microcredit market in a model with reversed asymmetric information hypothesis.

More precisely, in this paper we study how the MFI's decision to help (or follow-up) a client can impact borrowers' behavior. We provide a model where both the MFI - through a follow-up process - and the agent -through effort - can impact the probability of success of the project. Borrowers are heterogeneous on their risk which impacts their probability of success. The MFI decides which projects will be granted a loan. We first develop a theoretical model where both the MFI and the borrower are symmetrically informed about the probability of success of the project. The main result in this framework is that the optimal level of help chosen by the MFI is increasing with the risk of the borrower. Second, we develop a model under asymmetric information where the principal

(MFI) has information advantage on the probability of success. This is a rather realistic situation on the microcredit marked with an experienced MFI faced with an unexperienced borrower. Contrary to the first-best solution, under assymetric information we show that a non-monotonic trade-off between help and the type of the borrower is possible. Under asymmetric information the optimal level of help is first increasing with the ability of the agent, and beyond a certain threshold it decreases.

Finally, we test our results using trivariate models where we model simultaneously three processes (granting decision, follow-up decision, default event) to control for selection and endogeneity bias. To do so, we use data from a French MFI. We build a scoring model and identify how the decision to follow-up a client varies with the score. This relationship allows us to identify whether the "looking-glass self" phenomenon (which we explain bellow) is present in the decision to help a borrower. Empirical results support our theoretical findings: the optimal level of help seems to increase with the score of the borrower for low score agents. Conversely, for high score agents, the optimal level of help is decreasing with the score of the borrower.

On markets with imperfect information inefficiencies such as credit rationing may occur. Stiglitz and Weiss (1981) provide theoretical justification for credit rationing in a model with adverse selection. Microcredit partially responds to this problem as rationed and rejected borrowers may receive financing on the microfinance market after being denied access to financing by traditional banks.

Besides the decision of granting a loan to these rejected project holders the MFI my also decide to help them. From this perspective, our model can be interpreted in a venture capital framework where both the principal and the agent can provide effort to impact the probability of success of the project. Casamatta (2003) develops a double-sided moral hazard model with additive efforts and homogeneous agents. We add to this design heterogeneity among borrowers and reversed asymmetric information where the principal is the only player to observe the risk of the borrower.

Principal's superiority of information approach has been frequently used in academic literature. For instance, in insurance theory, Villeneuve (2000) studies pooling and separating equilibria in the context where the insurer evaluates risk better than its customers.

Another salient interdisciplinary contribution with reversed assymetric information is Benabou and Tirole (2003). Authors model the interactions between an agent with imperfect self-knowledge and an informed principal who chooses an incentive structure, such as offering rewards and threatening punishments or simply giving encouragement or providing help. Benabou and Tirole (2003) argue that by offering a low level of help, the principal signals that she trusts the agent who will attempt to infer principal's private information. According to the authors, in this situation help offered by others may be detrimental to one's self-esteem and create a dependence. Consequently, if no help is thought to be reserved for the high-ability micro entrepreneurs the MFI may choose not to help some very low ability micro entrepreneurs as well. Other situations where help can be detrimental to the agent are presented is Gilbert and Silvera (1996). Using different experiments authors show that help can be used to undermine the beliefs of the observers who might attribute a successful performance to help rather than to performer's abilities.

The phenomenon where the agent tries to infer principal's private information is called "looking-glass self" and was presented for the first time by Cooley (1902). In our model we attempt to capture the "looking-glass self" phenomenon on the microcredit market where the MFI may decide to provide help to borrowers. Thus, the principal's decisions will probably have an impact on borrowers' posterior beliefs.

The issue of borrower's self-esteem on the microcredit market is also discussed in Copisarow (2000). The author underlines that microcredits psychologically boost borrowers' self-confidence and self-esteem by giving them greater control over their lives and expanding their options. More generally, Copisarow (2000) argues that microfinance strongly contributes to the "psychological, social and financial well-being of micro-entrepreneurs". In our paper we don't study the impact of microcredit on borrower's self-esteem in itself. We rather focus on how the MFI takes into account the "looking-glass self" effect of training programs on borrowers' beliefs.

The academic literature on the effects of training programs in microfinance is relatively recent. For instance, Edgcomb (2002) summarizes the main findings of five grantees of FIELD (the Microenterprise Fund for Innovation, Effectiveness, Learning, and Dissemination) research on the relationship between " the characteristics of the clients and their business success" and the relationship of "business skills training and client success". Karlan and Valdivia (2011) study the effect of business training in FINCA-Peru, a group lending program designed for women by implementing a randomized control trial. They find a significant impact of training on client retention in the MFI, business knowledge improvement but little evidence on the profit or revenues increase. McKernan (2002) pioneers in measuring of the non credit effects of microcredit programs of three MFIs in Bangladesh providing noncredit services such as "social development programs".

In the empirical part of the paper we develop a credit scoring model. Credit scoring programs have been widely studied in academic literature. Meanwhile, the originality of the model presented in Boyes et al. (1989) is that they control for sample selection bias in a bivariate censored probit model. A solution to sample selection bias was provided for the first time by Heckman (1979) who proposed a two-stage estimator to estimate behavioral functions.

To ameliorate the bivariate probit model, Roszbach (2004) suggests modeling the survival time of a loan rather than the probability of default. The author develops a bivariate mixed model with a probit equation for the loan granting decision and loan survival time equation. We complete the bivariate probit model in Boyes et al. (1989) and the bivariate mixed model in Roszbach (2004) by adding a third equation for the follow-up decision.

The remainder of the paper is structured as follows. In section 2 we present the theoretical model. We first present the discrete type model, followed by continuous type model. Data used to test theoretical results is presented in section 3. In section 4 we present the econometric models which we used to estimate the empirical results presented in section 5. Section 6 concludes.

2 Theoretical Model

In this section we will develop a principal-agent problem with reversed asymmetric information. Borrowers' and MFI's payoffs are modeled akin to the fixed investment model with credit rationing presented in Tirole (2006). We assume that the borrower has no collateral to provide. First we present the discrete model with symmetric information where both the principal (the MFI) and the agent (the borrower) are informed about the ability of the borrower. Then, the discrete model with asymmetric information is presented. In this model the agent is not aware about his probability of success which is only observed by the principal. Second, we will present the continuous type model with symmetric and asymmetric information.

2.1 Discrete type model

The agent, he, has a project for which he needs financing. He has no collateral and no personal investment. Hence, he needs to borrow from the bank the total amount of the project, which we normalize to 1. The project will generate a return, ρ, in case of success and 0 in case of failure. The principal, she, demands a return of $R = 1 + r$ in case of success with $R < \rho$, where r is the fixed interest rate.[2] She receives 0 in case of failure. The intrinsic probability of success is denoted by θ_i. θ_i can be also interpreted as the ability of the borrower. We assume that there are three types of agents, $i \in \{L, M, H\}$ where $\theta_L < \theta_M < \theta_H$. The borrower may choose to provide a binary effort, $e \in \{0, 1\}$, at cost $\psi(e)$ where $\psi(0) = 0$ and $\psi(1) = \psi$. The principal, in addition to microcredit granting, may decide to provide binary help, $h \in \{0, 1\}$, at cost $c(h)$, where $c(0) = 0$ and $c(1) = c$.

[2] A fixed interest rate is consistent with data where the MFIs fix the same interest rate for all the borrowers.

In microfinance help may take different forms. Generally, microborrowers follow various trainings in accounting or business management which are organized by the MFI or by her partners. From the approach of the literature on double-sided moral hazard, help may be interpreted as the effort provided be the MFI. Both effort and help will increase the probability of success. We define the probabilities of success, $p_i(e,h)$, as follows:

$$p_i(0,0) \equiv \theta_i < p_i(1,0) < p_i(1,1) \quad \forall i$$
$$p_i(0,0) \equiv \theta_i < p_i(0,1) < p_i(1,1) \quad \forall i$$

2.1.1 Symmetric information

In this section, we consider a model where both the MFI and the borrower observe the type of the borrower. The timing is defined in Figure 1.

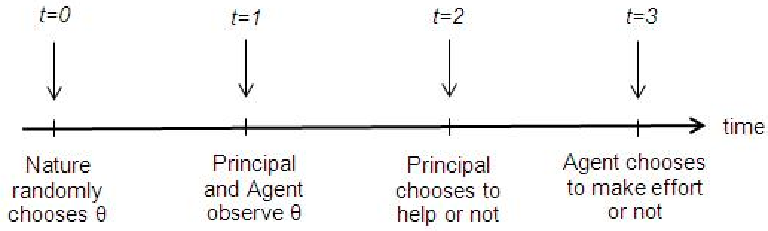

Figure 1: Timing of contracting under symmetric information

We make the following assumptions:

Assumption 1

The return of effort is increasing with type and effort is never done by the lowest type but always by the higher types:

$$p_L(1,h) - p_L(0,h) < \frac{\psi}{\rho - R} < p_M(1,h) - p_M(0,h) < p_H(1,h) - p_H(0,h) \quad \forall h$$

Assumption 2

The return of help is decreasing with type and it is never optimal to help the highest type but always the lower types:

$$p_L(e,1) - p_L(e,0) > p_M(e,1) - p_M(e,0) > \frac{c}{R} > p_H(e,1) - p_H(e,0) \quad \forall e$$

The perfect information equilibrium is such that the principal helps lower types, θ_L and θ_M and does not help the high type, θ_H. Both higher types, θ_M and θ_H make effort but the low type θ_L does not. In Figure 2 we present the extensive form of the game.

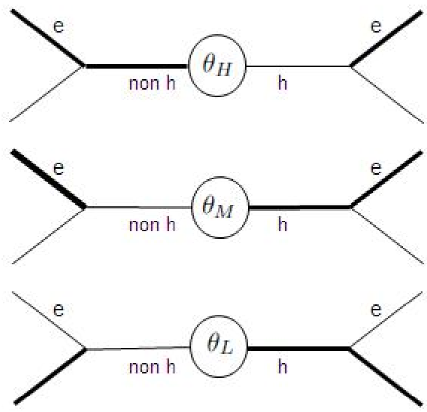

Figure 2: Symmetric Information

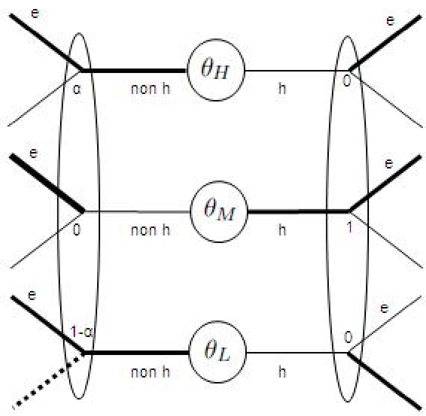

Figure 3: Asymmetric Information

2.1.2 Asymmetric information

Now assume that the agent is not aware about his type. The MFI is the only player to observe the type of the borrower. The action played by the principal (help or not) can be interpreted as a signal. The timing of contracting is defined in Figure 4.

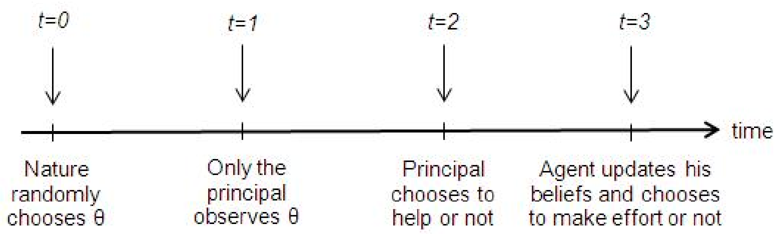

Figure 4: Timing of contracting under asymmetric information

We are looking for the perfect bayesian equilibrium (PBE) of this game. In a PBE agents form beliefs conditionally on the action taken by the principal and the resulting equilibrium must be compatible with these beliefs (for details on PBE see Osborne (2004), Fundenberg and Tirole (1991)). Let us show that the following PBE is possible: the principal helps only θ_M, and does not help θ_L and θ_H and everybody makes effort. We denote by α the probability to be θ_H among $\{\theta_L, \theta_H\}$. In other words, in this equilibrium, α is the belief of the agent that he is of high type when he observes that the principal chose to help him. When the agent observes that the principal decided not to help him he knows that his type is θ_M with certainty.

We make one additional assumption: the principal prefers a situation where the low ability agent exerts effort without help to a situation where a low ability agent exerts no effort and receives help. Formally:

Assumption 3 $p_L(0,1) - p_L(1,0) < \frac{c}{R}$

We have to check that it is optimal for the principal not to help if the agent is of type $\theta \in \{\theta_L, \theta_H\}$ and help if $\theta = \theta_M$. This equilibrium exists if, besides *Claim 3*, the expected return to the agent with effort and no help is greater than the relative cost of the effort:

$$(1-\alpha)(p_L(1,0) - p_L(0,0)) + \alpha(p_H(1,0) - p_H(0,0)) \geq \frac{\psi}{\rho - R}$$

The extensive form of the game is shown in Figure 3. In this equilibrium, due to the looking-glass self effect, the principal does not help the low ability agent to make him exert effort.

2.2 Continuous type model

Let us now study the robustness of the previous PBE in the continuous type model. We assume $\theta \in [0,1]$. The agent decides on the level of effort, $e \in [0,1]$ to provide which will positively impact the probability of success of the project. Borrower's disutility from effort is $\psi(e)$. In line with Casamatta (2003) and Brander and de Bettignies (2006) we assume that the disutility from effort is increasing and convex in e and $\psi(e) = \frac{e^2}{2}$. The principal, besides granting a loan, may decide to provide some level of help, $h \in [0,1]$, to the borrower. Help will increase the probability of success of the project and will generate a cost $c(h) = \frac{h^2}{2}$ to the principal.[3] In the continuous model, we assume that the probability of success is a function $P(e,h) = \theta e + (1-\theta)h$.[4] This specification captures the idea that effort will make more difference for a high ability agent, while help will have a stronger impact on a low ability agent. In other words, in line with Casamatta (2003), we assume that the joint realization of e and h is not required to implement the project. An important difference however, is that we assume that the probability of success is heterogeneous among borrowers, depending on their types, whereas Casamatta (2003) assumes that the probability of success is $\min\{e+h, 1\}$.

2.2.1 Symmetric information

In the continuous model where both the MFI and the borrower observe the type of the borrower, the timing of the game is the following. First, nature randomly selects the ability of the agent. Second, the agent and MFI discover the type of the borrower. Third, the MFI decides on credit

[3]Specifying the form of the cost function will not change the main results of our model which generally hold for any cost function which is increasing and convex in help.

[4]Note that we have always $P(e,h) = \theta e + (1-\theta)h \leq 1\ \forall h \in [0,1]$ and $\forall e \in [0,1]$

granting and follow-up. Finally, the agent decides on the level of effort.

We solve the program using backward induction. The agent chooses the optimal level of effort by maximizing his expected utility function, U_A:

$$U_A = (\theta e + (1-\theta)h)(\rho - R) - \frac{e^2}{2} \tag{1}$$

From the first order conditions we find the optimal level of effort chosen by the borrower:

$$e^*(\theta) = \theta(\rho - R) \tag{2}$$

Note that in symmetric information help does not impact the optimal level of effort. Given the optimal level of effort, the utility function of the principal is:

$$U_P = \left[\theta^2(\rho - R) + (1-\theta)h\right] R - 1 - \frac{h^2}{2} \tag{3}$$

The principal will maximize his utility function to choose the optimal level of help. The first order condition is:

$$(1-\theta)R = h^* \tag{4}$$

We can show that there exists a threshold for θ such that at the optimum the utility to the principal will be nonnegative.

Proposition 1

Under symmetric information, the optimal level of help provided by the MFI is monotonically decreasing with the ability of the borrower.

2.2.2 Asymmetric information

Under asymmetric information where only the MFI observes θ, the "looking-glass self" effect might occur. The agent observes the level of help chosen by the principal and he privately receives a signal σ, with conditional density $f(\sigma|\theta)$ which is common knowledge. The MFI does not observe σ. We assume that higher types of agents will receive higher signal σ according to the Monotone Likelihood Ratio Property. The borrower will try to interfere his type after observing the level of help chosen by the principal, i.e. the agent will try to estimate his type $\widehat{\theta}(h, \sigma) \equiv E(\theta|h, \sigma)$.

The timing of the game in asymmetric information is the following. First, nature randomly selects the type of the agent. Second, the MFI observes the type of the agent and the uninformed borrower privately learns an exterior signal σ. Third, the MFI decides on loan granting and help level, h. Then, the uninformed borrower observes h and updates his beliefs about his type $\hat{\theta}(h, \sigma)$. Finally, the agent choses the optimal level of effort e^*.

Note that in asymmetric information help will influence the optimal effort indirectly through $\hat{\theta}(\sigma, h)$. We will solve the problem by backward induction. The agent's payoff is

$$U_A = (\hat{\theta}(\sigma, h)e + (1 - \hat{\theta}(\sigma, h))h)(\rho - R) - \frac{e^2}{2} \tag{5}$$

The agent maximizes his utility function to choose the optimal level of effort:

$$e^* = \hat{\theta}(\sigma, h)(\rho - R) \tag{6}$$

The principal does not observe σ. Therefore, there is uncertainty on $\hat{\theta}(\sigma, h)$ for the principal. The MFI will only be able to use the conditional expectation $E(\hat{\theta}(\sigma, h|\theta))$ to estimate the level of effort chosen by the agent. The utility function of the principal is:

$$E_\sigma [U_P] = \left[\theta E(\hat{\theta}(\sigma, h)|\theta)(\rho - R) + (1 - \theta)h\right] R - 1 - \frac{h^2}{2} \tag{7}$$

where $E(\hat{\theta}(\sigma, h)|\theta) = \int_0^1 \hat{\theta}(\sigma, h) f(\sigma|\theta) d\sigma$. From the first order condition we find:

$$h^* = (1 - \theta)R + \frac{\partial E(\hat{\theta}(\sigma, h)|\theta)}{\partial h}\theta(\rho - R)R \tag{8}$$

where $\frac{\partial E(\hat{\theta}(\sigma,h)|\theta)}{\partial h}$ is the principal's expected update of borrowers' beliefs. Using the Implicit functions theorem in (8), we find:

$$\frac{\partial h^*}{\partial \theta} = -\frac{\frac{\partial^2 E(\hat{\theta}(\sigma,h)|\theta)}{\partial h \partial \theta}\theta + \frac{\partial E(\hat{\theta}(\sigma,h)|\theta)}{\partial h} - \frac{1}{\rho - R}}{\frac{\partial^2 E(\hat{\theta}(\sigma,h)|\theta)}{\partial h^2}\theta - \frac{1}{(\rho - R)R}} \tag{9}$$

According to the second order conditions, for a principal maximizing her utility function, the denominator in (9) has to be negative. This will be always the case if we assume $\frac{\partial^2 E(\hat{\theta}(\sigma,h)|\theta)}{\partial h^2} \leq 0$.

Proposition 2

The sign of $\frac{\partial h}{\partial \theta}$ will be the same as the sign of the numerator in (9).

In the following, we will study the sign of the numerator in (9) for different θ. To do so, we will define several conditions.

Condition 1

For low type borrowers, we have

$$\frac{\partial^2 E(\hat{\theta}(\sigma, h)|\theta)}{\partial h \partial \theta}\theta + \frac{\partial E(\hat{\theta}(\sigma, h)|\theta)}{\partial h} > \frac{1}{\rho - R} \tag{10}$$

One necessary condition for (10) to be true is that the left hand side of (10) has to be positive.

Condition 2

For high type borrowers, we have

$$\frac{\partial^2 E(\hat{\theta}(\sigma, h)|\theta)}{\partial h \partial \theta}\theta + \frac{\partial E(\hat{\theta}(\sigma, h)|\theta)}{\partial h} < \frac{1}{\rho - R} \tag{11}$$

A sufficient condition for expression (11) to be satisfied is that its left hand side has to be negative.

Condition 3

$$\frac{\partial^3 E(\hat{\theta}(\sigma,h)|\theta)}{\partial h \partial \theta^2} \cdot \frac{\theta}{\frac{\partial^2 E(\hat{\theta}(\sigma,h)|\theta)}{\partial h \partial \theta}} < -2$$

Under condition 3, the numerator in (9) is monotonically decreasing in θ. Condition 3 implies that the elasticity with respect to θ of the derivative of the principal's update, i.e. $\left[\left(\frac{\partial E(\hat{\theta}(\sigma,h)|\theta)}{\partial h}\right)'_{\theta}\right]$ has to be less than 2.

Proposition 3

Under asymmetric information, when conditions 1-3 are satisfied, there exists a threshold θ^* such that

1. *For $\theta \in [0, \theta^*)$, we have $\frac{\partial h}{\partial \theta} > 0$*

2. *For $\theta \in (\theta^*, 1]$, we have $\frac{\partial h}{\partial \theta} < 0$*

Note that we don't look for for a perfect bayesian equilibrium in the model with continuous type. The result in *Proposition 3* occurs due to the looking-glass self phenomenon. The principal knows that higher level of help will damage the expected type of the uninformed borrower, thus reducing the effort and the probability of success of the project. To avoid undermining very low ability agents, the MFI will choose not to help them. She is most likely to follow-up borrowers presenting an average risk. High-ability agents, on the other hand, do not need to receive any help, as their probability of success is sufficiently high.

3 Data

In the econometric model we explore if the "looking-glass self" effect operates as we have shown in the theoretical model, i.e. we will test if the probability to be helped is first increasing with risk and beyond some threshold it is decreasing.

Our data set consists of 782 applications for business microloans treated by a French MFI between May 2008 and May 2011. Business loans (up to 10,000€) are disbursed to micro-entrepreneurs who are rejected from the traditional credit market in order to create or develop their own business (self-employment).[5] We do not have information about the scoring models the MFI might have used in her decision process. The average amount of the approved loans was 8,900€, the average interest

[5]In contrast to Roszbach (2004) who studies consumer loans.

rate was 4,2%[6] and the mean maturity was 52 months. Table 1 shows the descriptive statistics and the definitions for the explanatory variables we use. Out of 782 applications, 365 (47%) were accepted and 417 (53%) were rejected. Among the accepted borrowers, 202 (55%) borrowers were followed-up. Follow-up decision can be interpreted as a decision to *help* the borrower. It can take the form of a training in accounting, business or staff management, etc.

To build a scoring model we need to identify which are the performing (i.e. "good") and non-performing loans (i.e. "bad" or "defaulted"). 21% of all the accepted borrowers had 3 or more delayed paiments in the credit history. In the following, we will denote these loans as defaulted loans.[7] This definition is inline with the MFI's policy. In general, the MFI writes-off all the loans having three or more consecutive delayed paiments.[8] Half of the defaulted loans have been followed-up (39 out of 79 loans). Whereas among performing loans a proportion of 57% was followed-up (163 out of 286 loans). Among the clients having received help, 81% (163 out of 202 loans) are still performing.

4 Econometric Model

The econometric model will allow us to test the non linear tradeoff between the probability to be followed-up and the risk of the borrower. To do so, we have to estimate three simultaneous processes. The first one models the credit granting decision on the binary decision variable (granted or not granted). The second one models the micro borrower follow-up decision given the loan was actually granted. These two processes are jointly described by a probit model.

One of the original parts of this model, directly related to the theoretical model, is the measure of defaulted payment risk among the main determinants of the follow-up decision. Actually, the theoretical model leads us to specify a non linear function of the default risk: we retained a quadratic form of the default risk measure. According to a rational expectation assumption, we build an ex-ante measure of risk which we include in the regression part. This measure is the conditional expectation of the default probability given observable covariates, directly related and deduced from the third process.

[6]The interest rate was fixed at 4% at the beginnign of the period and passed to 4.5% at the end of the period of analisys. The interest rate doesn't depend on borrower's characteristics.

[7]Note that the delayed payments need not to be consecutive or unpaid.

[8]Most of delayed paiments in the database where consecutive.

Table 1: Variables Definition and Descriptive Statistics

	Type of credit													
	Total		Rejected		Granted		No Follow-up		Follow-up		Bad		Good	
Variable definition	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Personal														
UNEMPL>12	0,39	0,49	0,44	0,50	0,33	0,47	0,28	0,45	0,37	0,48	0,42	0,50	0,31	0,46
Dummy: unemployed since >12 months														
DW	0,16	0,37	0,17	0,37	0,15	0,36	0,20	0,40	0,11	0,31	0,27	0,44	0,12	0,32
Dummy: widow(er) or divorced														
EDUCATION	1,84	1,36	1,80	1,36	1,89	1,36	1,89	1,30	1,89	1,40	1,46	1,17	2,01	1,38
Education level: 0-No qualification...5-Master degree														
MALE	0,62	0,49	0,63	0,48	0,61	0,49	0,60	0,49	0,62	0,49	0,75	0,44	0,58	0,49
Dummy: applicant is male														
PACSVM	0,21	0,53	0,18	0,50	0,24	0,56	0,18	0,46	0,29	0,62	0,14	0,45	0,27	0,58
Dummy: in a relationship other than marriage														
Household														
EXPENSES	0,45	0,49	0,45	0,50	0,45	0,49	0,42	0,45	0,47	0,52	0,47	0,42	0,44	0,51
Household monthly expenses (in thousands of euros)														
INCOME	1,33	1,14	1,19	1,10	1,49	1,16	1,33	1,06	1,61	1,23	1,11	0,80	1,59	1,23
Household monthly income (in thousands of euros)														
Business														
NOCONTRIB	0,30	0,46	0,34	0,48	0,26	0,44	0,27	0,45	0,25	0,44	0,38	0,49	0,23	0,42
Dummy: financial contribution to the business <5%														
CATERING	0,13	0,34	0,16	0,37	0,10	0,30	0,13	0,33	0,08	0,28	0,09	0,29	0,11	0,31
Dummy: the business is in the catering sector														
ASSETS	18,20	24,26	17,57	23,04	18,86	25,47	15,73	18,36	21,34	29,75	12,19	9,35	20,74	28,14
Business (in)tangible, financial assets (thous. euros)														
GMS	0,75	0,20	0,77	0,20	0,74	0,20	0,74	0,20	0,74	0,20	0,71	0,20	0,75	0,19
The ratio between the gross margin and the sales														
Other														
OTHERDEM	0,58	0,49	0,54	0,50	0,62	0,49	0,38	0,49	0,82	0,39	0,51	0,50	0,65	0,48
Dummy: the applicant has other credit demands														
HONORL	0,48	0,50	0,48	0,50	0,47	0,50	0,28	0,45	0,63	0,48	0,43	0,50	0,48	0,50
Dummy: the applicant has received a honor loan														
BANK	0,17	0,37	0,15	0,36	0,18	0,39	0,26	0,44	0,12	0,33	0,14	0,35	0,20	0,40
Dummy: the applicant was sent by a bank														
Number of observations	782		417		365		163		202		79		286	

Table 2: Descriptive statistics for survival time

				Percentiles							
Subsample	Mean	SD	Min	5	10	25	50	75	90	95	Max
T_i, bad loans	340.1	237	0	61	92	184	274	457	668	822	1156
T_i, good loans	469.5	327.8	31	92	123	214	365	638	1003	1095	1279

For the third part, given the loan was actually granted, the default risk is modeled using two alternative approaches. Following the traditional approach, we use the default event as a binary indicator which is described by a probit model. In this framework, we consider all defaulted loans to be similar. An alternative approach is to exploit the time elapsed before the occurrence of the defaulted payment. This approach takes into account the heterogeneity of the borrowers. It allows us to distinguish a good loan attached to a low default risk borrower from a recent loan for which a low risk of defaulted payment is simply due to the timing of the loan period (as we show latter, the default risk is increasing in time). To implement this approach we need to define the survival time which is the number of calendar days between the date of the first installment paid to the MFI and the date when a loan became defaulted. Descriptive statistics for survival time are given in Table 2. Using the survival time allows us to take into account the heterogeneity of the loan contracts which should be differentiated not only according to the moment where the contract is signed but also according to the length of the loan period.

To control the potential endogeneity of the follow-up decision and correct the potential sample selection bias, we use a common latent factor structure: the presence of a common latent factor within each error compound structure allows correlation among both decisions and the default event. Following Roszbach (2004) we use the same set of covariates in the first and in the second processes. The only additive factor we have to insert in the third process is the potential follow-up (decision) which should impact the defaulted payment risk and should contribute to reduce this risk.

4.1 Trivariate Probit Model (TPM)

In the TPM, the risk of the borrower is measured by his probability of default. We estimate the ex-ante risk of each borrower and study the relationship between the probability to be helped and the estimated risk. To do so, three probit equations are simultaneously estimated:

$$y_{1i}^* = w_i^{'}\beta_1 + \epsilon_{1i} \qquad y_{1i} = \begin{cases} 1 & if \quad y_{1i}^* > 0 \quad (Granted) \\ 0 & if \quad y_{1i}^* \leq 0 \quad (Otherwise) \end{cases} \tag{12}$$

$$y_{2i}^* = x_i^{'}\beta_2 + \alpha_1 R + \alpha_2 R^2 + \epsilon_{2i} \qquad y_{2i} = \begin{cases} 1 & if \quad y_{2i}^* > 0 \quad (Help) \\ 0 & if \quad y_{2i}^* \leq 0 \quad (Otherwise) \end{cases} \tag{13}$$

$$y_{3i}^* = w_i^{'}\beta_3 + \alpha_3 y_{2i} + \epsilon_{3i} \qquad y_{3i} = \begin{cases} 1 & if \quad y_{3i}^* > 0 \quad (Default) \\ 0 & if \quad y_{3i}^* \leq 0 \quad (Otherwise) \end{cases} \tag{14}$$

where $R \equiv \Phi(w_i^{'}\beta_3 + v_i)$ is the probability of default of the borrower (or the risk of the borrower) and $\Phi(\cdot)$ is the normal cumulative distribution function.

Loan granting decision is modeled in (12). w_i is a vector of different characteristics of the borrower, the household and the project.

The follow-up decision is modeled in the equation (13). Note that only borrowers with granted loans can be followed-up.x_i is a vector of variables concerning other credits and the origin of the borrower. We also add in the regression function a second order polynomial of the expectation of default risk. In this model, this is given by the probability that defaulted payment arises which will be determined by a set of covariates w_i and by an individual heterogeneity factor v_i justified later. Note that the independent variables in x_i should be different from the variables contained in w_i in order to ease identification problems. The estimates of the parameters assigned to $\Phi(w_i^{'}\beta_3 + v_i)$ and $\Phi(w_i^{'}\beta_3 + v_i)^2$ are the coefficients of our main interest in this paper, according to the theoretical model presented in section 2. If the results found in section 2 are empirically verified, we will expect α_1 to be positive and α_2 to be negative.

Equation (14) is the default equation. Default may occur only for granted loans, i.e. for $y_{1i} = 1$.

The presence of correlation among both decisions and the default event is allowed by imposing some structure on the error terms:

$$\begin{aligned} \epsilon_{1i} &= \rho_1 v_i + \epsilon_{1i}^0 \\ \epsilon_{2i} &= \rho_2 v_i + \epsilon_{2i}^0 \\ \epsilon_{3i} &= \rho_3 v_i + \epsilon_{3i}^0 \end{aligned}$$

where the components $\epsilon_{1i}^0, \epsilon_{2i}^0, \epsilon_{3i}^0$ are independent idiosyncratic parts of the error terms and each one is supposed to follow a normal distribution $N(0,1)$. The common latent factor v_i entering all the compound terms $\epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i}$ could be considered as an individual unobserved heterogeneity factor on the loan applicant ability to reimburse in time. Again, we assume that $v_i \sim N(0,1)$

and that this factor is independent of the idiosyncratic terms. The parameters ρ_1, ρ_2 and ρ_3 are free factor loadings which should be estimated. For identification reason, we impose the constraint $\rho_3 = 1$. Free factor loadings allow us to calculate the correlations between the error terms of the three equations.

Both the introduction of this common latent factor and the inclusion of the default risk expectation in the regression part of the second equation impose a simultaneous estimation and allow us to control and correct for the selection and endogeneity bias. By estimating jointly the credit granting decision with the rest of the processes, we allow to take into account the selection mechanism and avoid the potential bias related to that sample selection process. Finally, we maximize the log of the likelihood function which is presented in the Appendix.

4.2 Trivariate Mixed Model (TMM)

We extend the previous model by using additional information about the survival time of a loan T_i. In this model, the third process concerns the survival time before a defaulted payment arises rather than only the event of a defaulted payment. Let us define by t_i in the following way. For defaulted loans t_i is the number of days between the the date of loan granting and the date of the date of default. For performing loans t_i is the number of days between the the date of loan granting and the date of the reporting. The survival time is then either perfectly observed (not censored) when a defaulted payment occurs $y_{3i} = 1$, i.e. $T_i = t_i$ or is censored as the loan is still performing when $y_{3i} = 0$, i.e. $T_i > t_i$. The TMM model will allow us estimate the survival time for each individual. To do so, we assume that the survival time follows the Weibull distribution which is the most commonly used duration distribution in applied econometric work (Lancaster (1990)).

$$Ti|v_i, z_i, y_{2i} \sim Weibull(\lambda_i) \qquad \text{where } \lambda_i \equiv exp(z_i^{'}\beta_3 + \alpha_3 y_{2i} + v_i)$$

The expected survival time is given by:

$$E(T_i|z_i, y_{2i}, v_i) = \lambda_i^{-1}\Gamma(1 + \frac{1}{\sigma}) \tag{15}$$

where $\Gamma(.)$ is the complete Gamma function (for more details see Lancaster (1990), Appendix 1) and σ is the Weibull scale parameter. Consequently, the risk to default is necessarily related to the expectation of the survival time. Hence, a possible measure of this risk is naturally given by:

$$E(T_i|z_i, y_{2i}, v_i)^{-1} = \lambda_i \left[\Gamma(1 + \tfrac{1}{\sigma})\right]^{-1}$$

The process of loan granting remains unchanged. For the process of the follow-up decision, we replace the probability of default event by the alternative measure of risk, without the the current decision y_{2i} which should be obviously excluded from the set of covariates of the measure of the follow-up decision.

$$y_{2i}^{**} = x_i^{'}\beta_2 + \alpha_1 E(T_i|z_i, v_i)^{-1} + \alpha_2 E(T_i|z_i, v_i)^{-2} + \epsilon_{2i} \tag{16}$$

where $E(T_i|z_i, v_i) = exp(-z_i^{'}\beta_3 - v_i)\Gamma(1 + \frac{1}{\sigma})$.

For identification strategy, the expected survival time of a loan will be identified by using the observed survival time, censored or not, attached to the granted loans. By estimating simultaneously the three processes, we can avoid to bias the estimator of the variance of the parameters estimates related on this estimated expectation in the follow-up decision equation. The identification mechanism in both models is simply obtained by the non linear function of the linear combination of the determinants of risk default.

5 Empirical Results

The choice of the explanatory variables among all the available variables in the database took place in two stages. The first stage is very similar to the three-step procedure presented in Roszbach (2004). First, we checked for the univariate explanatory power of the appropriate variables for either of the two processes, loan granting decision and the survival time of the granted loans. Second, we verified for the eventual correlation between all the variables retained in step one. All the variables were uncorrelated or had a weak correlation. Third, we found the best two univariate equations for the loan granting decision (using a probit model) and the inverse of the survival time (using a duration model). To identify these "best" equations, we studied several criteria as t-statistics, loglikelihood value, AIC and BIC statistics, number of parameters and model stability. Finally the explicative variables we retained are unemployed for more than 12 months, divorced or widow(er), education level, gender, household expenses, household income, personal capital, economic sector, level of assets of the firm, gross margin on sales ratio. In the duration equation (equation ((15))), we additionally introduced the follow-up variable to control for the effect of *help* on individual's survival time.

One important originality of our econometric model consists in the second stage where we define the an additional process, the follow-up decision. To estimate the univariate equation for the follow-up decision we have first estimated the *Risk* defined by $E(T_i)^{-1}$ in the previous section for each individual. Next, we checked for the univariate explanatory power and the correlation between the variables which were not used in the previous two processes. We used a probit model to estimate the follow-up univariate equation. The regressors we finally retained are other demands for loans, being granted a "honor loan"[9], being sent by a commercial bank, being in a relationship other than marriage, $Risk$ and $Risk^2$. The estimates in the univariate equations are not efficient because the correlation between the error terms of the three processes is not taken into account. Moreover, the parameters estimated in the follow-up and the duration equation might suffer from sample selection bias as we do not observe these variables for rejected applicants. To deal with these issues, we will estimate the three equations simultaneously by maximizing the log of the likelihood function in a full information maximum likelihood (FIML) mixed model. To estimate the FIML mixed model, we need first to define the parameters starting values. The estimates of the parameters of FIML models and their standard errors are presented in Table 3 (bold shape is used to identify estimates significant at least at 10% level).

Table 3 is structured as follows. The first three columns present the three sets of parameter estimates for the loan granting process: the first is a univariate equation, the second presents the results for the TPM and the third presents the results for the TMM. We note that the variables being unemployed for more than 12 months, household expenses, household income, catering sector contribute significantly to the loan granting decision in each of the three models. On contrary, the non significance of the variables divorced or widow(er), level of education, gender, level of assets of the firm is confirmed whatever the model is. At first glance these results might appear inconsistent with the outcome one might expect to find. An explanation might be strong homogeneity in these variables. For example the great majority of the micro-borrowers in our sample have little or no education at all. The signs of most of the variables correspond well to their intuitive interpretation. However, the negative contribution of the Gross Margin on Sales ratio is less intuitive to understand. One plausible explanation could be the fact that the MFI is not taking this variable directly into account, but is rather focusing on the projected sales, which are strongly and negatively correlated with GMS ratio. We tried to introduce projected sales directly in the model. The corresponding parameter estimate was positive but non significant. It is worth noticing that the parameter estimates are very close in column (1) and (3) and that the significant estimates in column (2) are roughly a translation of the coefficients in (1) and (3).

Columns (4), (5) and (6) contain the three sets of parameter estimates for the follow-up decision for three different models. Having other loan demands or having received a honor loan are both

[9] A honor loan is a loan granted at a zero interest rate without any collateral required and subsidized by state. These honor loans were provided by organisms other than the MFI.

significant variables increasing the probability of being followed-up in all of the models. Applicants sent by a traditional bank are less likely to be followed-up according to the trivariate models. To explain this result we should consider that there is a stigmatization aspect taken into account by the MFI. For rejected borrowers the "looking-glass self" effect might operate very strongly, urging the MFI be less likely to assign them to training programs. In contrast, a relationship other than marriage seems to have no impact on the follow-up decision after correcting for the sample selection and endogeneity bias. As a whole, the estimates of the parameters seem to be underestimated in the univariate model in absolute value. They seem to be stronger in the TPM. The most interesting findings concern the estimates of the parameters of $Risk$ and $Risk^2$. Both estimates are non significant in the univariate equation, whereas they become significantly different from zero in the FIML models. The probability to help the micro-borrower seems to increase with his risk level, but less and less. To illustrate the existence of a return point using the TPM we need to study the sign of

$$\frac{\partial Pr(y_{2i}=1)}{\partial R} = \phi\left(x_i^{'}\beta_2 + \alpha_1 R + \alpha_2 R^2 + \epsilon_{2i}\right) \cdot (\alpha_1 + 2R\alpha_2)$$

Note that $\frac{\partial Pr(y_{2i}=1)}{\partial R}$ is of sign of $\alpha_1 + 2R\alpha_2$. The estimates in column (5) for $Risk$ and $Risk^2$ suggest that the probability to be followed-up is increasing for individuals with lower probability of default $R < 0.36$ and that it is decreasing for individuals with higher probability of default $R > 0.36$. Note that about 31% of granted loans had an estimated risk R higher than 0.36. Finally, given that a loan applicant had an estimated risk higher than 0.36, the probability of loan granting is 0.28.

Columns (7), (8) and (9) contain the three sets of parameter estimates for the scoring equations. Note that in the univariate model and the mixed model the risk is measured as the inverse of the expected survival time (the time before becoming a defaulted loan). In the TPM, the risk is defined as the probability to default. It is important to remark that if the MFI is optimally selecting her clients the signs of the parameters in columns (1), (2) and (3) have to be opposite to the signs of the parameters estimated in columns (7), (8) and (9). This is generally the case. Nevertheless, according to our model the MFI does not significantly employ the variables divorced or widow(er), education level, gender and assets of the firm in her selection process, whereas these variables have a significant impact on individual's performance. One possible explanation is that the MFI providing data is not choosing its clients in a perfectly optimal way. Roszbach (2004) arrives at similar conclusions, arguing that some of the variables significantly impacted the survival time but were not significant in the credit-granting equation. The salience of the follow-up process on borrowers' performance is proved in column (9). The estimator has always a negative sign but it is only significant in the TMM. Our intuition is that the TPM model reflects the decision process used by the MFI. Indeed, banks are more likely to use scoring models based on probit equations rather than duration equations. Nevertheless, our results suggest that follow-up has a more important impact on the survival time. In our opinion, the TMM model perhaps better captures the real effect of help on risk, as duration equations allow taking into account the heterogeneity among the defaulted loans. Consequently, we can conclude that in the full information model with survival time, help significantly decreases the risk of the borrowers after correcting for sample selection and the endogeneity bias.

Moreover, we observe that the Weibull parameter is always significant and greater than 1 suggesting that in our sample the hazard increases monotonically with time.

Finally, the TPM seems to better correspond to the means the MFI actually uses in her decision processes (scoring models relying on the probability of default rather than survival time models). However, only the mixed model using the survival time proves the significant impact of the training programs.

6 Conclusion

In this paper we provide a theoretical model for the "Looking-glass self" effect on the microcredit market in the developed countries. In the theoretical model we show that whereas the relationship between help and the type of the borrower is always decreasing in symmetric information, this is not necessarily the case under asymmetric information.

We have tested these findings using data from a French MFI which in addition to financial services provided training programs. Using trivariate models to control for endogeneity and sample selection bias, we partially confirmed this result: the MFI seems to take into account the stigmatization effect of help.

Our model provides interesting evidence on how MFI's decisions might undermine agent's intrinsic motivation. However, further research is required to better understand the conditions on the shape of the beliefs and on how the principal estimates the expected type of the borrower.

Another limit concerns the role of agent's effort in the empirical model. While in the theoretical model effort and risk of the borrower can be dissociated, in the empirical model this is not the case. In further research it will be worth studying at which moment the effort is playing a role, given ex-post vs ex-ante equations.

Table 3: Univariate and Trivariate MLE of Loan Granting, Follow-up, Survival Time and Default Equations

	Loan Granting Decision			Follow-up Decision			Risk equation		
		Trivariate:	Trivariate:		Trivariate:	Trivariate:		Trivariate:	Trivariate:
	Univariate	3 probits	mixed	Univariate	3 probits	mixed	Univariate	3 probits	mixed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	**0,64**(0,25)	**1,48**(0,65)	**0,61**(0,25)	**-1,25**(0,12)	**-0,75**(0,32)	**-1,00**(0,22)	**-6,83**(0,5)	0,22(0,51)	**-6,83**(0,47)
UNEMPL>12	**-0,28**(0,10)	**-0,69**(0,28)	**-0,27**(0,11)				**0,44** (0,20)	**0,36**(0,21)	**0,79**(0,22)
DW	-0,04(0,13)	-0,35(0,40)	-0,05(0,14)				**0,53**(0,22)	**0,89**(0,24)	**0,40**(0,21)
EDUCATION	-0,02(0,04)	-0,08(0,09)	-0,01(0,04)				**-0,21**(0,09)	-0,09(0,08)	**-0,26**(0,09)
MALE	-0,12(0,10)	-0,36(0,26)	-0,13(0,10)				**0,56**(0,23)	**0,86**(0,22)	**0,63**(0,19)
EXPENSES	**-0,23**(0,12)	**-0,58**(0,34)	**-0,22**(0,12)				**0,68** (0,25)	**0,91**(0,26)	**0,57**(0,18)
INCOME	**0,11**(0,05)	**0,30**(0,15)	**0,11**(0,05)				**-0,24**(0,13)	**-0,47**(0,13)	-0,12(0,13)
NOCONTRIB	**-0,20**(0,11)	-0,41(0,28)	**-0,21**(0,11)				**0,58**(0,21)	0,34(0,23)	**0,65**(0,17)
CATERING	**-0,41**(0,16)	**-1,14**(0,48)	**-0,41**(0,16)				0,27(0,34)	**0,68**(0,39)	0,32(0,30)
ASSETS	0,003(0,002)	0,01(0,01)	0,003(0,002)				**-0,02**(0,01)	**-0,03**(0,01)	**-0,02**(0,01)
GMS	**-0,50**(0,25)	-0,93(0,6)	**-0,45**(0,26)				**-0,97** (0,49)	-0,79(0,51)	-0,61(0,41)
FOLLOW-UP							-0,01(0,19)	-0,25(0,27)	**-0,54**(0,22)
OTHERDEM				**0,68**(0,13)	**1,20**(0,24)	**1,10**(0,18)			
HONORL				**0,28**(0,12)	**0,60**(0,19)	**0,55**(0,17)			
BANK				-0,19(0,15)	**-0,63**(0,22)	**-0,53**(0,2)			
PACSVM				**0,18**(0,1)	0,22(0,16)	0,23(0,15)			
Risk				0,00(0,00)	**3,84**(2,2)	**2,14**(0,95)			
Risk2				0,00(0,00)	**-5,37**(3,22)	**-0,86**(0,5)			
rho1		**-2,89**(1,27)	-0,08(0,20)						
rho2					0,45(0,4)	0,04(0,23)			
sigma							**1.24**(0,12)		**2,22**(0,38)
Observations	669	662	662	662	662	662	337	662	662
Log Likelihood	-464	-777	-1251	-401	-777	-1251	-206	-777	-1251

References

BENABOU, R. and TIROLE, J. (2003), "Intrinsic and Extrinsic motivation" , Review of Economic Studies, 70, 489-520

BRANDER, J.A. and DE BETTIGNIES, J.-E. (2006), "Financing entrepreneurship: Bank finance versus venture capital", Journal of Business Venturing, 22, 808832

BOYES, W., DENNIS L. Hoffmann and STUART A. Low (1989), "An Econometric Analysis of the Bank Credit Scoring Problem", Journal of Econometrics, 40, 3-14

CASAMATTA, C (2003), "Financing and Advising: Optimal Financial Contracts with Venture capitalists", The Journal of Finance Vol LVIII NO.5, 2059-2085

COOLEY, C. (1902), Human nature and social order, (New York: Scribner's)

COPISAROW, R. (2000), "The application of microcredit technology to the UK: key commercial and policy issues", Journal of Microfinance Volume 2 number 1

EDGCOMB, E. (2002), "What makes for effective microenterprise training?", Journal of Microfinance Volume 4 number 1

FUNDENBERG, D. and TIROLE, J. (1991), Game Theory, (Cambridge, MA: MIT Press)

GILBERT, D. and SILVERA, D. (1996), "Overhelping", Journal of Personality and Social Psychology, 70, 678-690

GREENE, W. (1993), Econometric Analysis, 3rd ed. (New Jersey: Prentice-Hall, Inc.)

HECKMAN, J. J. (1979), "Sample Selection Bias as a Specification Error", Econometrica, 47, 153-161

KARLAN, D. and VALDIVIA, M.(2011), "Teaching Entrepreneurship: Impact of business training on Microfinance Clients and Institutions", The review of Economics and Statistics, Vol. 93, No. 2, Pages 510-527

LANCASTER, T. (1990), The Econometric Analysis of Transition Data, (Cambridge University Press)

McKERNAN, S.M. (2002), "The impact of microcredit programs on self-employment profits: do non credit program aspects matter?", The Review of Economic Statistics, 84(1): 93-115

OSBORNE, M.J. (2004), An Introduction to Game Theory, Oxford University Press

Rapport annuel 2010 de l'Observatoire de la microfinance, Banque de France

ROSZBACH, K. (2004), "Bank lending policy, credit scoring, and the survival of loans", The Review of Economics and Statistics, 86(4), 946-958

STIGLITZ, J. E. and WEISS, A. (1981), "Credit Rationing in Markets with Imperfect Information", American Economic Review, 71, 393-410

TIROLE, J. (2006), The Theory of Corporate Finance, (Princeton and Oxford: Princeton University Press)

VILLENEUVE, B. (2000), "The Consequences for a monopolistic Insurance Firm of Evaluating risk better than Customers : The adverse selection hypothesis reversed", The Geneva Papers on Risk and Insurance Theory, 25: 65-79

A Trivariate Probit Model: likelihood function

The individual contribution to the likelihood function given the common factor v_i can be written as follows:

$$Li(\theta|y_{1i}, y_{2i}, y_{3i}, w_i, x_i, z_i, v_i) = \underbrace{\Phi\left(w_i^{'}\beta_1 + \rho_1 v_i\right)^{y_{1i}}}_{P(y_{1i}=1|v_i,...)} \cdot \underbrace{\left[1 - \Phi\left(w_i^{'}\beta_1 + \rho_1 v_i\right)\right]^{(1-y_{1i})}}_{P(y_{1i}=0|v_i,...)} \cdot$$
$$\underbrace{\Phi\left(x_i^{'}\beta_2 + \alpha_1\Phi(z_i^{'}\beta_3 + v_i) + \alpha_2\left[\Phi(z_i^{'}\beta_3 + v_i)\right]^2 + \rho_2 v_i\right)^{y_{1i}y_{2i}}}_{P(y_{2i}=1|v_i,y_{1i}=1,...)} \cdot$$
$$\underbrace{\left[1 - \Phi\left(x_i^{'}\beta_2 + \alpha_1\Phi(z_i^{'}\beta_3 + v_i) + \alpha_2\left[\Phi(z_i^{'}\beta_3 + v_i)\right]^2 + \rho_2 v_i\right)\right]^{y_{1i}(1-y_{2i})}}_{P(y_{2i}=0|v_i,y_{1i}=1,...)} \cdot$$
$$\underbrace{\left[\Phi(z_i^{'}\beta_3 + \alpha_3 y_{2i} + v_i)\right]^{y_{1i}y_{3i}}}_{P(y_{3i}=1|v_i,y_{1i}=1,y_{2i},...)} \cdot \underbrace{\left[1 - \Phi(z_i^{'}\beta_3 + \alpha_3 y_{2i} + v_i)\right]^{y_{1i}(1-y_{3i})}}_{P(y_{3i}=0|v_i,y_{1i}=1,y_{2i},...)}$$

Hence, in the first model with three simultaneous probit equations we finally have to integrate L_i with respect to the density function of v_i: By using the adaptive Gaussian quadrature integral approximation, we maximize the log of the likelihood function.

$$\begin{aligned} & l(\theta|y_{1i}, y_{2i}, y_{3i}, w_i, x_i, z_i) \\ = & \sum_{i=1}^{n} \ln\left(\int Li(\theta|y_{1i}, y_{2i}, y_{3i}, w_i, x_i, z_i, v_i)\phi(v_i)dv_i\right) \end{aligned}$$

B Trivariate Mixed Model: likelihood function

The individual contribution to the likelihood function conditional on v_i using loan survival time can be written as follows:

$$
\begin{aligned}
& Li(\theta | y_{1i}, y_{2i}, y_{3i}, t_i, w_i, x_i, z_i, v_i) \\
= \; & \underbrace{\Phi\left(w_i^{'}\beta_1 + \rho_1 v_i\right)^{y_{1i}}}_{P(y_{1i}=1|v_i,\ldots)} \cdot \underbrace{\left[1 - \Phi\left(w_i^{'}\beta_1 + \rho_1 v_i\right)\right]^{(1-y_{1i})}}_{P(y_{1i}=0|v_i,\ldots)} \\
& \underbrace{\Phi\left(x_i^{'}\beta_2 + \alpha_1 E(T_i)^{-1} + \alpha_2 E(T_i)^{-2} + \rho_2 v_i\right)^{y_{1i}y_{2i}}}_{P(y_{2i}=1|v_i,y_{1i}=1,\ldots)} \\
& \underbrace{\left[1 - \Phi\left(x_i^{'}\beta_2 + \alpha_1 E(T_i)^{-1} + \alpha_2 E(T_i)^{-2} + \rho_2 v_i\right)\right]^{y_{1i}(1-y_{2i})}}_{P(y_{2i}=0|v_i,y_{1i}=1,\ldots)} \\
& \underbrace{\left[\sigma \lambda_i^{\sigma} t_i^{\sigma-1} exp\left\{-\left(\lambda_i t_i\right)^{\sigma}\right\}\right]^{y_{1i}y_{3i}}}_{f(t_i|v_i,y_{1i}=1,y_{2i},\ldots)} \underbrace{\left[exp\left\{-\left(\lambda_i t_i\right)^{\sigma}\right\}\right]^{y_{1i}(1-y_{3i})}}_{P(T_i>t_i|v_i,y_{1i}=1,y_{2i},\ldots)}
\end{aligned}
$$