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Abstract

The microcredit market, where inexperienced micro-borrowers meet experienced microfinance institutions (MFIs), is subject to reversed asymmetric information. Thus, MFIs' choices can shape borrowers' beliefs and their behavior. We analyze how this mechanism may influence microfinance institution decisions to allocate business training. By means of a theoretical model, we show that superior information can lead the MFI not to train (or to train less) riskier borrowers. We then investigate whether this mechanism is empirically relevant, using data from a French MFI. Confirming our theoretical reasoning, we find a non-monotonic relationship between the MFI's decision to train and the risk that micro-borrowers represent.

Keywords: microcredit, reversed asymmetric information, looking-glass self, bivariate probit, scoring model

JEL Codes: C34, C41, D82, G21

1 Introduction

Microcredit is a small-scale financial tool designed for individuals who are rejected by the conventional financial market. Micro-borrowers are often unemployed, lack collateral and have no experience starting a business. After having been widely used and studied in developing countries, microcredit is now widespread in developed countries. While its main objective – poverty alleviation – applies to both types of economies, its implementation involves several particular features in the developed countries. For example, individual lending is prevalent[2] and loans do not specifically target women in the industrialized economies. Another important characteristic of microfinance in the developed countries is its use of formal business training including Business Development Services. European Microfinance Institutions have been involved in business training since their emergence.[3] Business training refers to various additional non-financial support services that accompany loans. They may consist of defining and developing the business project (assessing profitability, defining a business strategy and financing needs, administrative help), information and help with obtaining financing, courses in accounting, management, marketing and law, and the monitoring of the project. Here, using a theoretical model and empirical evidence (data from a French MFI), we investigate how an MFI assigns borrowers to training programs.

Preliminary descriptive statistics suggest that individuals assigned to training are not riskier ex-post than individuals without training: the default rate for borrowers receiving business training is 19% against 25% for the others. This evidence reflects two possible scenarios: either training is targeted toward (ex-ante) high-risk individuals and is highly efficient (as ex-post borrowers with training are not riskier than borrowers without training) or training is not targeted exclusively toward high-risk borrowers and is not highly efficient. The literature is agnostic about the efficiency of training in

[2]Group lending is a well-known lending methodology in microfinance which is particularly successful in rural environments with tightly-knit networks (Postelnicu et al. 2014). Nevertheless, in developing countries an increasing number of MFIs have begun to implement individual lending (Armendariz and Morduch 2010).

[3]see Lammermann et al. (2007)

microfinance.[4] Studies in both developed and developing economies fail to corroborate the first scenario, where business training is mainly targeted toward the riskiest individuals and is highly efficient. This lends credence to the second scenario, where business training is not necessarily allocated to the riskiest borrowers. The rationale behind assignment to training is therefore somewhat puzzling, and the aim of this paper is to explore whether the MFI's superior information may explain this puzzle. Generally, MFIs finance first-time micro-entrepreneurs who need financial backing to start a business, and who usually lack the necessary experience. It is therefore plausible that the microfinance institutions are better informed than the micro-entrepreneurs about the potential of the project, for example due to their past experience. In this case, the contract offered by the MFI (assignment to a training program or not) can reveal information to the borrower about himself, and thus impact his actions. This mechanism, termed looking-glass self (Cooley 1902), provides a rationale for the hypothesis where the MFI, having superior information, might indeed not exclusively allocate business training to high risk individuals.

To explore this further, we build a theoretical model in which an MFI has superior information about the risk of borrowers (*i.e.* the intrinsic probability that their project will fail). Its choice on training impacts borrowers' beliefs and shapes their behavior. In this context, we reveal the existence of equilibria where assignment to business training is not a monotonic function with respect to borrowers' risk. We provide a theoretical model where both the MFI - through business training - and the borrower - through effort - can impact the probability of success of the project. In cases where, under symmetric information, the level of training chosen by the MFI is increasing with a borrower's risk, we show that reversed asymmetric information can lead to a non-monotonic relationship between business training and the risk of the borrower's project. In particular, we show that there exists a Perfect Bayesian Equilibrium where the optimal level of business training is a

[4] See for example Karlan and Valdivia (2011) or Lensink et al. (2011) for developing countries; and Balkenhol et al. (2013), Evans (2011) or Edgcomb (2002) for developed countries

non-monotonic concave function of risk: at first the optimal level of business training is increasing with the risk of the borrower, and then beyond a certain threshold, it is decreasing.

Our empirical findings corroborate the existence of such a non-monotonic relationship. We develop a credit scoring model using a bivariate probit model where we control for individual unobserved heterogeneity. We first estimate borrowers' intrinsic risk by means of a probit regression. Then, using the simplest form of non-linearity, by introducing the estimated risk and its square term in the business training probit regression, we find that, at first, the probability of being assigned to a business training is increasing with borrowers' risk, and then beyond a certain threshold, it is decreasing. This result is, moreover, robust to controlling for selection bias (Heckman 1979; Boyes et al. 1989) and to the use of the inverse of the survival time of the loan, instead of the probability of default, as an alternative measure of borrowers' risk (Roszbach 2004).

Our analysis contributes to three strands of the literature: the theoretical effect of reversed asymmetric information, the role of training programs in microfinance and the empirics of scoring models. The looking-glass self effect occurs when the social environment attempts to manipulate self-perception. This phenomenon has been widely studied in the sociological literature. The term "looking-glass self" was first introduced by Cooley (1902), who argued that people obtain a sense of who they are by observing how others perceive or treat them. In economics, this concept was first introduced by Benabou and Tirole (2003a) and Benabou and Tirole (2003b). Benabou and Tirole (2003b) state that for the looking-glass self effect to impact the agent's behavior, the principal must have private information relevant to the agent's behavior and the agent must be aware of the principal's superior information and objectives. Benabou and Tirole (2003a) study various situations where the principal might be better informed than the agent (for example at school, in the labor market and in the family) and also consider the case of an informed principal choosing a level of help to provide to the agent.[5] In their model, however, the agent has to choose whether to undertake the task or not conditional on a private signal and on the level of help chosen by the principal. In contrast, in this paper we consider that the agent chooses a level of effort that positively impacts the probability of success of the project.

The notion of informed principal was introduced by Myerson (1983) and Maskin and Tirole (1990). However, it is only relevant in specific contexts. Ishida (2006) uses a model with an informed principal to show that promotions in the labor market can be used strategically in the presence of the looking-glass self effect. Villeneuve (2000) studies pooling and separating equilibria in a context where the insurer evaluates risk better than its customers. Swank and Visser (2007) show how delegation and increased attention from an informed employer can improve the motivation of an uninformed employee. Nevertheless, these authors point out that their model only fits situations where the agent is at the beginning of his career or is performing tasks for the first time in his life, whereas the principal has previous experience with similar tasks or agents. This is remarkably like the microcredit market situation, where micro-entrepreneurs borrow from an experienced MFI to start a business for the first time. To the best of our knowledge, this paper is the first to introduce the notion of informed principal to the credit market.

To confirm the plausibility of the non-monotonic relationship between training assignment and borrowers' risk highlighted in our theoretical model, our empirical strategy is based on a bivariate probit model. We jointly model two probit equations. The first equation estimates the training assignment process. The second equation estimates the probability of default by the borrower. A comparable bivariate probit model was developed by Boyes et al. (1989), where the two probit equations concern the loan granting process and default by borrowers. To address the selection bias issue in our setting (Heckman 1979), our paper pioneers the development of a trivariate probit model

[5]Other situations where help, in general, can be detrimental to the agent are presented by Gilbert and Silvera (1996). Using different experiments, the 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 the performer's abilities.

to test for the robustness of our baseline bivariate probit model. The empirical literature moreover argues that despite defaults, some loans may still be profitable, if the default occurs sufficiently late. The bank might then be more concerned about the timing of a default than the default itself. Roszbach (2004) addresses this issue by providing a survival time model. In line with this study, we use an alternative measure of risk in a bivariate mixed model to check for the robustness of our findings. The original feature of our paper lies in the developing formal empirical models, taking into account endogeneity issues, selection bias or the survival time of the loans, to study how an MFI assigns different borrowers to training programs.

Regarding the empirical effect of training on default, we find a mitigated impact on probability of default, but a significant positive impact on survival time. These contrasting results are in line with previous empirical findings in both developing and developed countries. Karlan and Valdivia (2011), for example, find a significant impact of training on client retention and business knowledge improvement but little evidence of impact on profit or revenue increase in FINCA-Peru. On the other hand, McKernan (2002) finds that noncredit aspects of microfinance in developing countries (group cohesion, joint liability and social development programs) have positive effects on borrowers' profits. In developed countries, Evans (2011) underlines some positive outcomes for business training under the Women's Initiative for Self Employment in the US, whereas Edgcomb (2002) reports mixed results on correlations between completed training and successful entrepreneurship outcomes for five case studies in the US.

The remainder of the paper is structured as follows. In section 2 we present the theoretical model. We first present the discrete borrower type model, followed by the continuous type model. Data used to corroborate theoretical results is presented in section 3. In section 4 we present the econometric model which we used to estimate the empirical results outlined in section 5. We check for robustness of our results in section 6. Section 7 concludes.

2 Theoretical model

2.1 General framework

The agent, a borrower, has a project for which he needs financing. He has no collateral and no personal investment. He needs to borrow from the bank the total amount of the project, which we normalize to 1. The project generates a return, ρ, in the case of success and 0 in the case of failure. The principal, an MFI, demands a return of $R = 1 + r$ in the case of success with $R < \rho$, where r is the fixed interest rate. A fixed interest rate is consistent with data used in the empirical part of the paper, in which the MFI fix the same interest rate for all borrowers. The MFI receives 0 in the case of failure. The probability of success (denoted $p(\theta, e, h)$) depends on borrower type θ, borrower effort e and level of business training from the MFI h.[6] We assume the probability of success to be increasing in these three terms. θ can also be interpreted as the intrinsic probability of success, depending on borrowers' and projects' characteristics and excluding the effects of business training and effort (*i.e.* $p(\theta, 0, 0) = \theta$). Effort is costly for the borrower and business training is costly for the MFI. The respective costs are denoted by $\varphi(h)$ and $\psi(\theta, e)$ (*i.e.* we allow the cost of effort to be type-dependent). The purpose of this paper is to analyze the relationship between borrower type θ and level of allocated training h. We therefore abstract from the approval process, as business training is only granted to accepted borrowers. Moreover, we assume that once a borrower is accepted, the MFI maximizes profit – or minimizes loss – on this borrower (although it can have a different objective function in the approval process). The objective function of the MFI is therefore given by

$$U_P = p(\theta, e, h)R - \varphi(h)$$

[6] In the context of microfinance, business training may take different forms. Generally, micro-borrowers follow various courses in accounting or business management organized by the MFI or by its partners. From the approach of the literature to double-sided moral hazard (Casamatta 2003; De Bettignies and Brander 2007), business training may be interpreted as the effort provided by the MFI.

and the utility of the borrower is given by:

$$U_A = p(\theta, e, h)(\rho - R) - \psi(\theta, e)$$

We follow the standard approach in banking modeling by assuming that the MFI is risk neutral. To simplify the model, we additionally assume that the borrower is risk neutral.[7] We analyze two information structures. In the first one, the information is perfect and symmetric: both the borrower and the MFI observe borrower type θ. The MFI chooses h and the borrower chooses e simultaneously.

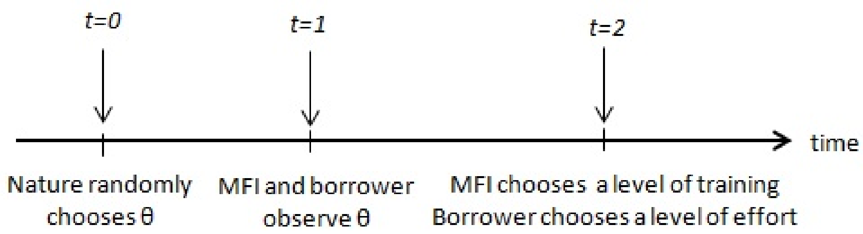

Figure 1: Timing of contracting under symmetric information

Our aim is to determine whether reversed asymmetric information can lead the MFI not to provide business training to the weakest types of borrowers, *i.e.* the riskiest borrowers. We will focus on cases where, under perfect information, the MFI provides a level of business training decreasing with type. This means that, in the absence of the looking-glass self effect, the allocation of business training might be considered as bad news for borrowers (as it would reflect a low probability of success).

In the second configuration, we assume reversed asymmetric information, that is, a situation where the borrower does not know his type, while the MFI does. As pointed out in the introduction, this informational setting is particularly relevant for the microcredit market, where inexperienced

[7]However, relaxing this second assumption and modeling a concave utility function $U_A(\cdot)$ for the agent would not change our result as long as $U_A(0) = 0$.

borrowers meet experienced MFIs. In this case, the level of business training chosen by the MFI (h) also conveys information about the borrower's type and might influence the borrower's behavior. In other words, by observing h, the borrower forms a belief about his type that leads him to some level of effort. When choosing h, the MFI internalizes this mechanism, that shapes its profit through borrower's effort.

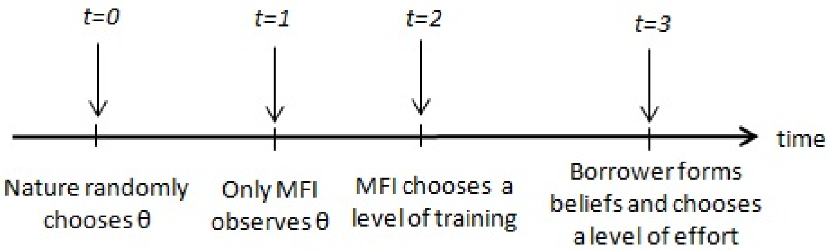

Figure 2: Timing of contracting under asymmetric information

We show that, unlike the symmetric information case, there can be a non-monotonic (concave) relationship between business training and borrower type, in some Perfect Bayesian Equilibria (PBE). The empirical section then seeks to confirm this peculiar feature of business training.

To build our theoretical argument, we present a discrete and a continuous model. Both models have advantages and drawbacks. The discrete model wins out on simplicity and can be used to illustrate the main mechanisms at work. It additionally enables us to compare the payoffs to the MFI under symmetric and reversed asymmetric information and to provide conditions under which the MFI is better-off when it has superior information. The continuous model has the disadvantage of being more complex; however, its advantage lies in being a better match for our empirical exercise, where borrower type and business training provision are modeled as continuous variables.

2.2 The main mechanisms: A discrete illustration

We first give the basic intuitions of our model through a simple discrete model ($e \in \{0,1\}$, $h \in \{0,1\}$) with three types of borrowers, that we will call weak-, medium- and strong-type borrowers:

$\theta \in \{\theta_W, \theta_M, \theta_S\}$. Let $\psi(\theta, 0) = 0\ \forall\theta$, $\psi(\theta, 1) = \psi\ \forall\theta$, $\varphi(0) = 0$ and $\varphi(1) = \varphi$. Borrowers' types are defined by the return on effort and business training. We make the following assumptions:

A1: The return on effort is increasing with type: $[p(\theta, 1, h) - p(\theta, 0, h)]$ is increasing with θ, $\forall h$.

A2: The return on business training is decreasing with type: $[p(\theta, e, 1) - p(\theta, e, 0)]$ is decreasing with θ, $\forall e$.

A3: The weak-type borrowers do not have the incentive to provide effort (whatever the level of business training):

$$p(\theta_W, 1, h) - p(\theta_W, 0, h) < \frac{\psi}{\rho - R} < p(\theta_M, 1, h) - p(\theta_M, 0, h) \quad \forall h$$

A4: The MFI is not interested in training the strong-type borrowers:

$$p(\theta_M, e, 1) - p(\theta_M, e, 0) > \frac{\varphi}{R} > p(\theta_S, e, 1) - p(\theta_S, e, 0) \quad \forall e$$

Our second assumption corresponds to Assumption 3 in Benabou and Tirole (2003a), while the third and fourth assumptions are made to render our problem non trivial.

Remark 1. *This setting leads to a situation where, under symmetric information, the MFI provides business training to the two weakest types: θ_W and θ_M, and does not provide business training to the strongest type: θ_S. Borrowers of types θ_M and θ_S provide effort but the weak type θ_W does not.*

Under reversed asymmetric information, the borrower is not aware of his type. Only the MFI observes it. The MFI's action (assignment to business training or not) may therefore convey information to the borrower, who will form beliefs about his type after having observed the MFI's decision on business training.

Our aim is to show that there exists a Perfect Bayesian Equilibrium in which assignment to business training is a non-monotonic function of borrower type, that is, in which the MFI only trains borrowers of type θ_M. In this case, a borrower observing that he is not being trained infers that he is either of weak (θ_W) or strong (θ_S) type. Let us note α the probability that the borrower is θ_S when he receives no business training from the MFI ($(1-\alpha)$ is the probability of being θ_W). In other words, α represents the borrower's belief that he is strong-type when he observes that the MFI chooses not to train him. Moreover, in the equilibrium considered, when the borrower observes that the MFI has decided to train him he is certain that he is type θ_M. This leads to the following proposition:

Proposition 1. *Under reversed asymmetric information, there exists a PBE where the MFI only helps θ_M-type borrowers and all borrowers exert effort, if and only if:*

$$(1-\alpha)\left[p(\theta_W,1,0)-p(\theta_W,0,0)\right]+\alpha\left[p(\theta_S,1,0)-p(\theta_S,0,0)\right]\geq\frac{\psi}{\rho-R} \tag{1}$$

This PBE is preferred by the MFI if:

$$p(\theta_W,0,1)-p(\theta_W,1,0)<\frac{\varphi}{R} \tag{2}$$

Condition (1) ensures that a borrower observing he is not being helped optimally exerts effort, whereas condition (2) states that the MFI prefers a situation where weak-type borrowers exert effort without being helped to one of equilibrium with symmetric information (where the weak-type borrower does not exert effort but receives help).

The intuition behind this result is rather simple. In the highlighted PBE, the MFI uses its superior information to induce the weak-type borrowers to exert effort. It does so by pooling them with the strong-type borrowers, those for whom effort is the most profitable. This is done at the expense of not providing them with business training, which is worth it under condition (2).

2.3 The continuous model

Let us now turn to a richer model with a continuum of types, effort and business training: $\theta \in [0,1]$, $e \in [0,1]$ and $h \in [0,1]$. In this case, we assume – for the sake of simplicity – that the impact of business training or effort on probability of success is decreasing with borrower type:

$$p''_{1j} < 0 \qquad for \quad j = 2,3$$

For the explicit form that we consider in this section, we specifically assume

$$p(\theta, e, h) = \theta + (1-\theta)\frac{1}{2}(e+h). \tag{3}$$

This form is in line with our definition of θ corresponding to the intrinsic probability of success and with the literature on venture capital (Casamatta 2003), according to which effort and business training are perfect substitutes in terms of their impact on probability of success. Consistent with the discrete model above, optimal effort will be increasing with borrower type, due to a "discouragement" effect: a borrower who "realizes" or is led to believe he has a low intrinsic probability of success will be discouraged from exerting effort. This effect will be captured in our model through a type-specific cost of effort. More precisely, we need $\psi(\theta, e)$ to be such that $E(\theta, h) = \arg\max_e [p(\theta, e, h)(\rho - R) - \psi(\theta, e)]$ is increasing in θ. One very simple way to model this property – which keeps the model tractable – is to assume a linear effort with respect to borrower type $E(\theta, h) = \gamma\theta$. This is in line with the economic literature in which the principal has a vested interest in boosting the agent's self-esteem in order to increase his motivation (Benabou and Tirole 2002; Ishida 2006). Taking probability of success as defined in (3), this optimal effort can be obtained, for instance, by assuming $\psi(\theta, e) = \frac{\rho - R}{4\gamma}\frac{1-\theta}{\theta}e^2$.

Regarding the cost of business training incurred by the MFI, a quadratic form $\varphi(h) = \frac{ch^2}{2}$ (where c is a positive constant) will be enough to ensure that the optimal level of business training is decreasing with type under symmetric information.

Indeed, under symmetric information, the program of the MFI is given by:[8]

$$\begin{cases} & h^*(\theta) & = & \underset{h \in [0,1]}{\arg\max} \left(\theta + \frac{1}{2}(1-\theta)(e+h)\right) R - \frac{1}{2}ch^2 \\ s.t. & e & = & \gamma\theta \end{cases}$$

Under this setting the following remark holds:

Remark 2. *Under symmetric information, the optimal level of business training provided by the MFI is decreasing with borrower type:*

$$h^*(\theta) = \frac{R}{2c}(1-\theta)$$

In other words, the MFI provides business training to those who need it most. The optimal level of business training is a decreasing affine function of borrower type.

Let us now turn to the case of reversed asymmetric information. Importantly, our aim is to show that (in a situation where the level of business training is decreasing with type under symmetric information) superior information may lead the MFI to train the weakest-type borrowers less. In the case of a continuum of types, this would correspond to a non-monotonic (concave) relationship

[8]Note that we do not model the approval process. Therefore, we do not make any assumption on the MFI's position regarding profits. Consequently, our model is applicable both to non-profit NGOs and to for-profit commercial organizations.

between business training and type, *i.e.* an "exotic" pooling Perfect Bayesian Equilibrium in which several non-adjacent values of θ are associated with the same level of business training. Let us show that such an equilibrium is possible.

Consider that business training is a concave non monotonic function of type $h^*(\theta)$ such that a level of business training h is associated with two possible types $\underline{\theta}(h)$ and $\overline{\theta}(h)$ (except at its maximum). A borrower observing a given level of business training infers some information about his type. The inferred borrower type writes:

$$t_\theta(h) = \frac{\underline{\theta}(h) f_\theta\left(\underline{\theta}(h)\right) + \overline{\theta}(h) f_\theta\left(\overline{\theta}(h)\right)}{f_\theta\left(\underline{\theta}(h)\right) + f_\theta\left(\overline{\theta}(h)\right)}$$

where $f_\theta\left(x\right)$ represents the belief of a type θ borrower on the distribution of types. This will consist in a Perfect Bayesian Equilibrium if the optimal business training strategy when the borrower's inferred type is $t_\theta(\cdot)$ is precisely $h^*(\theta)$, that is if h^* is the solution of:

$$\begin{cases} & h^*\left(\theta\right) & = & \underset{h\in[0,1]}{\arg\max}\left(\theta + \frac{1}{2}\left(1-\theta\right)\left(e+h\right)\right)R - \frac{1}{2}ch^2 \\ \text{s.t.} & e & = & \gamma t_\theta(h) \end{cases}$$

The borrower updates his beliefs after having observed the level of business training chosen by the MFI. This occurs due to the looking-glass self effect. The MFI is aware of the borrower's updating process. This mechanism is reflected in the constraint on borrower's effort in the MFI's maximization program. The borrower's effort depends on the updated type rather than on the true type, which is not observed by the borrower.

Proposition 2. *There exists a PBE in which business training is a non-monotonic concave function of type. It notably requires that borrowers' beliefs are decreasing with type: a high level of business training is bad news for strong-type borrowers but a good news for weak-type borrowers.*

To prove that this equilibrium exists, we analyze a particular concave business training function, symmetric with respect to $\frac{1}{2}$: $h^* = \sigma\theta(1-\theta)$. In this case, the MFI offers the same level of business training h to borrowers of type:

$$\underline{\theta}(h) = \frac{1}{2} - \sqrt{\frac{1}{4} - \frac{h}{\sigma}} \quad \text{and} \quad \overline{\theta}(h) = \frac{1}{2} + \sqrt{\frac{1}{4} - \frac{h}{\sigma}}$$

and (type-dependent) distributions of beliefs of the form:

$$f_\theta(x) = 1 - \frac{\sigma}{\gamma}(\theta - 1)\left(x - \frac{1}{2}\right)$$

will lead to a Perfect Bayesian Equilibrium. Indeed, the inferred borrower type writes:

$$t_\theta(h) = \frac{1 - 2(\theta - 1)\left(\frac{1}{4}\frac{\sigma}{\gamma} - \frac{h}{\gamma}\right)}{2}$$

such that the optimal level of business training which is a solution of

$$\begin{cases} \max\limits_{h \in [0,1]} & \left(\theta + \frac{1}{2}(1-\theta)(e+h)\right)R - \frac{1}{2}ch^2 \\ s.t. & e = \gamma t_\theta(h) \end{cases}$$

writes $h(\theta) = \frac{R}{2c}\theta(1-\theta)$, which corresponds to the business training function $h^*(\theta)$ with $\sigma = \frac{R}{2c}$. In this equilibrium, the beliefs of borrowers correspond to distorted uniform distributions: distorted upward for types $\theta < 1/2$ and distorted downward for types $\theta > 1/2$. Thus, for strong-type borrowers business training is bad news, whereas it is good news for weak-type borrowers: for a given level of business training, weak-type (resp. strong-type) borrowers put more weight on the higher (resp. lower) corresponding type. This allows the MFI to increase the level of effort provided by weaker-type borrowers, by pooling them with stronger-type borrowers.

The above is intended to show that there exist Perfect Bayesian Equilibria in which business training is a non-monotonic function of borrower type. There may be many other PBEs in the considered setting, and a lot of other settings in which the highlighted PBE exists. We do not address multiplicity here. Rather, in the remainder of the paper, we present an empirical strategy that illustrates the relevance of the featured equilibrium.

We emphasized in this theoretical section that, because of superior information, a microfinance institution might not want to train (or might want to train less) the weakest-type borrowers. This is because the MFI knows that its business training decision conveys information about the borrower type. By pooling the weakest-type borrowers with strongest-type borrowers, the MFI uses the "looking-glass self" effect to induce them to exert more effort.

In the following section we provide the institutional context of the MFI providing data for our study, which we present in section 4. In section 5 we describe the econometric model aimed at analyzing the relationship between assignment to business training and borrower type (measured by their risk or ex-ante intrinsic probability of default). The econometric exercise will allow us to analyze whether the MFI internalizes the fact that its business training decision impacts borrowers' behavior through the "looking-glass self" effect.

3 Institutional context of the MFI

CREASOL, the MFI providing data for our study, was created in 2006 in the South of France as a non-profit NGO, at the initiative of a commercial bank under its corporate social responsibility scheme. This MFI generally targets individuals who have difficulty accessing financial services from mainstream banks, mainly residing in the Provence-Alpes-Côte-d'Azur region. In line with its social mission statement, most of the MFI's clients are (long-term) unemployed, have low education and income levels and are starting a business for the first time in their lives. Most of them are seeking to become self-employed to escape unemployment and/or poverty. The MFI does not require any collateral or guarantees from its clients, which means the total pool of applicants of this MFI is considered "too risky" by most commercial banks.

In addition to microcredit services, this MFI is highly active in business training provision. Information is available on *all* the applicants who were granted a microcredit between May 2008 and May 2011,[9] as well as on business training provision when loans were granted. To our knowledge, the MFI's borrowers where not given any training other than that mentioned in the MFI's data set. The MFI's clients include almost equal numbers of individuals receiving and not receiving training (55% and 45% respectively). We have no evidence that the MFI choices to train primarily riskiest clients. Unfortunately, we do not have data on business development (ex. profits, sales, etc.), which is only available in forecast form during the application stage, via a business plan presented by the applicant. Hence, we cannot investigate the link between business training provision and business development. Nevertheless, our data set contains information on borrowers' ex-post repayment behavior to the MFI. We observe the number and dates of unpaid installments, enabling us to test for the presence of a non-linear relationship between business training provision and the borrower type (*i.e.* likelihood of success) illustrated in the theoretical model.

Each individual can apply only once for a microcredit. This MFI aims at financial inclusion of all borrowers after granting the first microcredit.[10] The timing of the relationship between the MFI and the borrower is the following. First the borrower applies for a loan. Then, the MFI decides whether to accept or reject the borrower's application. The decision process involves several stages. First, the loan officer presents the project during a credit committee meeting. Second, the credit committee takes the decision to grant the loan or not. Third, the MFI decides whether or not

[9] Our sample covers the universe of applicants.

[10] As a consequence, the MFI does not provide dynamic incentives through progressive lending.

to provide training to the selected applicants. Training is mandatory for the selected borrowers, who cannot refuse to participate. We then observe for each client his/her microcredit repayment behavior, *i.e.* the number and dates of unpaid installments.

4 Data

Using CREASOL data, we model three different (consecutive) processes:

1. Granting of loan
2. Assignment to business training
3. Defaulting on three or more installments.

Table 1 gives the descriptive statistics for our data along with the t-tests to compare different groups means. Information on 782 applicants for a business loan was collected between May 2008 and May 2011.[11] The vast majority of these loans was for a business start-up or buy-out, rather than for business development. The average amount of the loans approved was €8,900, the average interest rate was 4.2%[12] and the mean maturity was 52 months.

[11] We do not study consumer loans, in contrast to Roszbach (2004).

[12] The interest rate was fixed at 4% per year at the beginning of the period and reached 4.5% at the end of the period of analysis. The interest rate is fixed and hence does not depend on borrower characteristics.

Table 1: Descriptive Statistics

	Applicants				Borrowers					
Variables	**Total**	**Granted**	**Rejected**	**t-test**	**Training**	**No Training**	**t-test**	**Defaulting**	**Performing**	**t-test**
Granted (%)	0.47									
Business training (%)	0.26	0.55						0.49	0.57	-0.08
High risk (%)	0.10	0.22			0.19	0.25	-0.05			
Individual Characteristics										
Male (%)	0.62	0.61	0.63	-0.02	0.62	0.60	0.02	0.75	0.58	0.17***
Education (no. of diplomas)	1.84	1.89	1.80	0.09	1.89	1.89	0.00	1.46	2.01	-0.55***
Single (%)	0.55	0.53	0.57	-0.04	0.50	0.57	-0.07	0.63	0.51	0.13**
Unemployed more than 12 months (%)	0.39	0.33	0.44	-0.11***	0.37	0.28	0.08*	0.42	0.31	0.11*
Household Characteristics										
Household income (kEUR)	1.33	1.49	1.19	0.30***	1.61	1.33	0.29**	1.11	1.59	-0.49***
Household expenses (kEUR)	0.45	0.45	0.45	-0.01	0.47	0.42	0.06	0.47	0.44	0.03
Business Characteristics										
Low personal investment (%)	0.30	0.26	0.34	-0.08**	0.25	0.27	-0.02	0.38	0.23	0.15***
Assets (kEUR)	18.20	18.86	17.57	1.28	21.34	15.73	5.62**	12.19	20.74	-8.55***
Food and accommodation sector (%)	0.13	0.10	0.16	-0.06**	0.08	0.13	-0.04	0.09	0.11	-0.02
Gross margin/Sales	0.75	0.74	0.77	-0.03*	0.74	0.74	0.00	0.71	0.75	-0.03
Other Characteristics										
Other applications (%)	0.58	0.62	0.54	0.08**	0.82	0.38	0.44***	0.51	0.65	-0.15**
Honor loan (%)	0.48	0.47	0.48	-0.01	0.63	0.28	0.36***	0.43	0.48	-0.05
Sent by a mainstream bank (%)	0.17	0.18	0.15	0.03	0.12	0.26	-0.14***	0.14	0.20	-0.06
No. of observations	782	365	417		202	163		79	286	

47% of the applicants were granted a microcredit between May 2008 and May 2011. Data on rejected applicants is used to correct for selection bias in a robustness check. Our data set is unusual in providing information on rejected applicants.

Table 1 shows that the proportion of long-term unemployed applicants (more than 12 months) is significantly greater among rejected projects. There is also a significantly greater proportion of applicants with low personal investment (lower than 5%),[13] projects in the food and accommodation sector, projects having a high ratio of gross margin to sales. On average, accepted applicants come from households with higher incomes.

55% of the accepted borrowers were assigned to a business training program.[14] The individual characteristics of borrowers assigned and not assigned to training do not appear to differ much. Nevertheless, a few differences deserve mention. The proportion of long-term unemployed individuals is greater for borrowers assigned to business training. Moreover, they have higher household incomes and their businesses have higher asset levels. Individuals assigned to business training are more likely to have made other applications and to have been granted honor loans.[15] This differentiation is consistent with a microcredit setup where NGOs providing training programs also provide honor loans: the variable "Other applications" often includes ongoing applications for an honor loan. Hence, there is a direct link between the two variables and the likelihood of being assigned to business training. These additional financing sources appear to be important factors in the MFI's decision to assign a borrower to a training program. Interestingly, applicants sent by a mainstream bank are less likely to be assigned to a training program. This is in line with

[13]Low personal investment is a dummy taking value 1 if the applicant's personal financial contribution to the project is lower than 5% of the project size. We use this cut-off because it is the lowest available in our data after "No personal investment", and very few applicants provided no personal investment.

[14]Assignment to a training program can be interpreted as treatment and borrowers can be divided into a treated and control group respectively. From this perspective, our paper fits into the literature studying treatment effects. Nevertheless, treatment is obviously not randomly assigned in our case.

[15]An honor loan is an interest-free loan subsidized by the French government for individuals willing to start a business in order to become self-employed. The government delegates the disbursement of these loans to NGOs, which may also provide training programs.

our intuition. Borrowers sent by a mainstream bank either have a co-financing loan from the bank (these are potentially "strong-type" clients) or have been rejected (these are potentially "weak-type" clients). Our model predicts that both strong-type and weak-type clients are the least likely to be trained.

To build a scoring model, we define as "defaulting" borrowers with 3 or more unpaid installments in their credit history within the MFI. In other words, we use data on ex-post defaults by the MFI's clients. 22% of all the accepted borrowers had 3 or more delayed payments in their credit history. These loans will be termed as "defaulting" in the remainder of the paper.[16] This definition mirrors the MFI's actual policy: it generally writes off all loans involving three or more consecutive delayed payments. 19% of the clients receiving business training are defaulting clients, against 25% for clients not receiving business training. However, this difference is not significant according to the t-test. Almost half the defaulting loans were assigned to a training program, whereas 57% of performing loans were assigned to a training program, but this difference is not significant either.

As Table 1 illustrates, there are significant differences between defaulting and performing clients. These differences are usually (with some exceptions) of opposite sign to those for the approval decision. This outcome is an indicator of the quality of the MFI's loan granting process. Defaulting clients are more likely to be male, single, and long-term unemployed, with lower education, income levels, personal investment and assets. All these variables will be taken into account for in the design of the risk measure presented in the next section.

Descriptive statistics on the intrinsic borrower risk, modeled by a simple probit equation, are given in Table 2. We note that the average predicted intrinsic risk for the entire pool of applicants is 0.24. Naturally, it decreases for accepted applicants to 0.22. These relatively high levels of risk are handled by the MFI partly with the support of the government through (indirect) subsidies

[16] Note that the delayed payments need not be consecutive or remain unpaid. However, most delayed payments in the database were consecutive.

(Bourlès and Cozarenco 2014).

Table 2: Descriptive statistics on predicted intrinsic risk of the applicants

	Mean	Min	Max	SD
Accepted applicants	0.22	0	0.69	0.17
Rejected applicants	0.26	0	0.82	0.19
Total pool of applicants	0.24	0	0.82	0.18

In the next sections we use this data to test for the presence of the looking-glass self mechanism pointed out in our theoretical model.

5 Econometric model

This section examines the relationship between borrower type and likelihood of being assigned to a training program by the MFI. The borrower's "type" in the theoretical model, *i.e.* the intrinsic probability of a business succeeding, corresponds in practice to the score given by the MFI to each applicant during the approval process. However, because we do not have any information on this score, we use the information on the ex-post defaults of the borrowers which is available from the MFI. The aim is to use *ex-post* information on credit history to estimate the *ex-ante* score given by the MFI, assuming that the MFI's scoring strategy is based on its previous experience. To proxi borrower type, we use a probit equation that estimates the likelihood of a borrower defaulting.[17] Among the explanatory variables, we include individual, household and business characteristics. In addition, we control for business cycles[18], which obviously impact the likelihood of defaulting. An unfavorable economic environment during the start-up phase can jeopardize a business's chances of surviving. We therefore include quarterly rates of increase in business failures (as a measure of economic health) and in new business start-ups (as a measure of competition) at the time the loan

[17] DeYoung et al. (2008) show that credit scoring mitigates the information asymmetries associated with geographically distant small business borrowers.

[18] Source: Fiben, Banque de France.

is granted (and one and two quarters latter) for each micro-enterprise in our sample, according to its sector of activity. Data for business cycles exclusively cover the French PACA Region, the region where our MFI operates.

As in the theoretical model, in addition to the individual, household and business characteristics that are the components of θ, ex-post default depends on business training provision (h) and on borrower's effort (e). We will attempt to isolate these three effects (θ, h, e). To identify the effect of business training, we introduce into the default equation a dummy taking value one if a borrower receives business training and zero otherwise. To isolate the effect of effort on the likelihood of defaulting, we will introduce a form of heteroscedasticity depending on business training and on borrower's education level into the default equation, using a bivariate probit model.

This approach allows us to estimate the variable *Risk* depending solely on individual, household, and business characteristics to proxy the borrower type in the theoretical model. The variable *Risk* therefore corresponds to $1 - \theta$ in our theoretical model. However, the interpretation of the PBE equilibrium outlined in the theoretical model is not altered by this inversion: the non-monotonic concave relationship between business training and type θ corresponds by symmetry to a non-monotonic concave relationship between *Risk* and business training. We will therefore test the following hypotheses:

H1: The likelihood of receiving business training is increasing with risk for low-risk borrowers.

H2: The likelihood of receiving business training is decreasing with risk for high-risk borrowers.

To test this non-linear relationship between the likelihood of receiving business training and borrower type, as suggested by the theoretical framework, we include the predicted *Risk* and $Risk^2$ variables in the business training equation. More precisely, we jointly model two processes, business training decisions and the probability of defaulting under unobserved individual heterogeneity. We control for unobserved individual heterogeneity, taking into account the "soft" information about borrower type (motivation, skills, personality, etc.), collected by the MFI during face-to-face meetings. The joint modeling allows us to control for endogeneity of business training in the default equation. Isolating the effect of business training in the default equation, moreover, provides a better estimation of the intrinsic probability of default, *i.e.* a better proxy for borrower type.

Furthermore, the heteroscedasticity of the model captures the idea that observing the same level of business training can trigger different inference mechanisms in two different borrowers. In other words, the inference process introduces noise into a borrower's behavior (or effort), and thereby engendering noise in his likelihood of defaulting, which implies higher and non-constant variance. This can naturally be represented by a scedastic function attached to the unobservable variable, v_i. By introducing heteroscedasticity into the default equation, we isolate the impact of effort on the probability of defaulting.

Thus, controlling for endogeneity and introducing heteroscedasticity help disentangle three different effects discussed in the theoretical model: the effect of training, borrower's effort and borrower type. Our bivariate model writes as follows:

$$y_{1i}^* = \beta_1 x_i^{'} + \lambda_1 Risk + \lambda_2 Risk^2 + \epsilon_{1i} \qquad y_{1i} = \begin{cases} 1 \quad if \quad y_{1i}^* > 0 \quad Business \ \ training \\ 0 \quad if \quad y_{1i}^* \leq 0 \quad Otherwise \end{cases} \tag{4}$$

$$y_{2i}^* = \beta_2 w_i^{'} + \eta \mathbf{B}_i + \alpha_1 y_{1i} + \epsilon_{2i} \qquad y_{2i} = \begin{cases} 1 \quad if \quad y_{2i}^* > 0 \quad Default \\ 0 \quad if \quad y_{2i}^* \leq 0 \quad Otherwise \end{cases} \tag{5}$$

where x_i is a vector of variables specific to the business training decision, w_i is a vector of various controls composed of individual, household and business characteristics and $\mathbf{B}_i$ is a vector of variables measuring the business cycle of the sector of activity of enterprise i. It includes rate of increase in business failures and in new business start-ups in enterprise i's sector of activity, at the time of approval and one and two quarters after approval.

The correlation between the business training decision and defaulting is modeled by imposing the following structure on the error terms:

$$\begin{aligned} \epsilon_{1i} &= \rho_1 v_i + \epsilon^0_{1i} \\ \epsilon_{2i} &= \rho_{2i} v_i + \epsilon^0_{2i} \end{aligned}$$

where the components $\epsilon^0_{1i}, \epsilon^0_{2i}$ are independent idiosyncratic parts of the error terms and each is assumed to follow a normal distribution $\mathcal{N}(0,1)$. The common latent factor v_i in the compound terms ϵ_{1i} and ϵ_{2i} could be considered as an individual unobserved heterogeneity factor. We assume that $v_i \sim \mathcal{N}(0,1)$ and that this factor is independent of the idiosyncratic terms. $\rho_{2i} \equiv \rho_2 exp(\alpha_2 y_{1i} + \delta Education_i)$, meaning that business training indirectly impacts the probability of defaulting through α_2 (inference effect). We moreover assume that the inference process depends on the borrower's education level (or skills), through the coefficient δ, which also represents the indirect effect of education on the probability of defaulting.

The parameters ρ_1 and ρ_2 are free factor loadings which should be estimated. For identification reasons, we impose the constraint $\rho_2 = 1$. Hence, borrower type is proxied by $Risk = \Phi(w_i'\hat{\beta}_2 + v_i)$, where $\Phi(\cdot)$ is the normal cumulative distribution function and $\hat{\beta}_2$ is estimated using equation (5). Therefore $Risk$ is the estimated intrinsic probability of the borrower defaulting.[19]

For model identification, it is important to ensure that the variables in the x_i vector are different from the variables in the w_i vector. As described in the Data section, the three variables "Honor loan", "Other applications" and "Sent by a mainstream bank" are directly linked to the business training process. Hence, we use these three variables exclusively in the business training equation. We use business cycle indicators in the default equation to ensure full identification of our model; the rate of increase in business failures and in new businesses start-ups at the outset of the micro-

[19] By intrinsic probability of defaulting we mean the probability of defaulting "cleaned" of the effect of business training and borrower's effort.

enterprise (*i.e.* at the beginning of loan, and one and two quartes after the beginning of loan). These cannot be used in the training equation, as they occur after assignment to training.

Like in the theoretical model, this model is estimated only for granted loans, as an individual can only be assigned to a training program if he has actually been granted a microcredit. Hence, we do not account for selection bias in the bivariate probit model, selection bias correction being left to robustness exercise.

We maximize the log of the likelihood function which is the sum of individual contributions to likelihood (see Appendix A). The starting values for the bivariate probit model, which can also be consulted for benchmarking purposes, are given by the univariate estimation presented in Table 7, in Appendix D.

6 Econometric results

The estimations for the bivariate heteroscedastic probit model are presented in Table 3.[20]

The non-linear relationship between the likelihood of receiving business training and borrower type is shaped by the coefficients of $Risk$ and $Risk^2$. The $Risk$ loading is positive in all the specifications and the loading of the quadratic term is always negative, suggesting that the MFI is more likely not to provide business training to borrowers representing a very low or a very high risk; the probability of receiving business training is first increasing with risk and then, beyond a certain threshold, decreasing with risk. This relationship is significant at 1% level. We can compute, using the estimators in column (1), the risk threshold beyond which the probability of receiving business training begins to decrease with risk. To do so we use the derivative:

$$\frac{\partial Pr(y_{1i}=1|x_i, Risk, v_i)}{\partial Risk} = (\hat{\lambda}_1 + 2\hat{\lambda}_2 Risk)\phi(\cdot)$$

[20] In this paper we are interested in the signs of the loadings and not the sizes of marginal effects. Hence all results presented are estimated coefficients rather than marginal effects.

where $\phi(\cdot)$ is a normal density which is always positive. Hence the sign of the previous derivative is given by $\hat{\lambda}_1 + 2\hat{\lambda}_2 Risk$. It will be positive for $Risk$ smaller than 0.35 and negative otherwise. We estimated the $Risk = \Phi(w_i'\hat{\beta}_2 + v_i)$ for each *accepted* client in our dataset. 77% have an estimated risk lower than 0.35 and 23% have an estimated risk higher than this threshold. The estimated probability of receiving business training as a function of the estimated risk of the borrowers is presented in Figure 3.

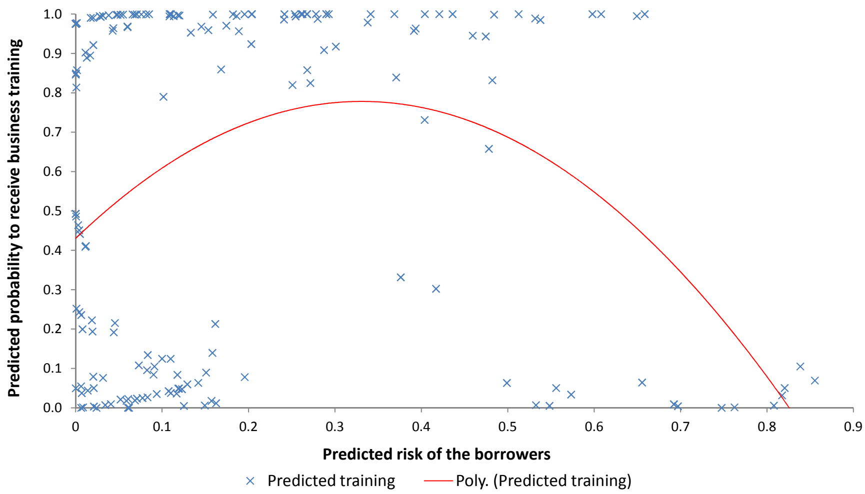

Figure 3: Bivariate Probit Model Estimations

Table 3: Determinants of Business Training and Default Processes

Model	Bivariate probit			
	(1)		(2)	
Dependent variable:	Business training		Default	
Explanatory variables:				
Risk	24.71***	(9.56)		
Risk^2	-35.61***	(13.34)		
Other applications	3.52***	(1.3)		
Honor loan	1.46***	(0.54)		
Sent by a mainstream bank	-1.76**	(0.73)		
$\hat{\rho}_1$	1.53**	(0.63)		
Business training (direct effect)			-0.33	(0.23)
Male			0.84***	(0.12)
Education (direct effect)			-0.11*	(0.04)
Single			0.33***	(0.12)
Unemployed at least 12 months			-0.06	(0.1)
Household income (kEUR)			-0.5***	(0.11)
Household expenses (kEUR)			0.81***	(0.15)
Low personal investment			0.2*	(0.11)
Assets			-0.04***	(0.01)
Food and accommodation sector			0.96***	(0.14)
Gross margin/Sales			-0.64**	(0.26)
Rate of increase in failures beginning of loan			0.009	(0.006)
Rate of increase in failures beginning of loan +1Q			0.01*	(0.005)
Rate of increase in failures beginning of loan +2Q			0.004	(0.007)
Rate of increase in new start-ups beginning of loan			0.015***	(0.004)
Rate of increase in new start-ups beginning of loan +1Q			0.005	(0.004)
Rate of increase in new start-ups beginning of loan +2Q			-0.002	(0.005)
Business training (indirect effect)			1.00**	(0.47)
Education (indirect effect)			-0.68*	(0.36)
Intercept	-3.15***	(1.18)	-0.27	(0.29)
-2 Log Likelihood	653			
Observations	340			

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

concave curve is a second degree fit curve for the predicted data. For the 23% of clients having a risk level above the 0.35 threshold, the likelihood of being assigned to a training program is decreasing with $Risk$, as the MFI is concerned about the negative impact business training might have on their inferred type.

Regarding other control variables in the business training equation we observe a highly significant positive relationship between business training and other applications and honor loan. Being sent by a mainstream bank, however, is negatively associated with the likelihood of receiving business training. Individuals sent by a mainstream bank have either been rejected by the mainstream bank (and are likely high risk) or have been granted a co-financing credit by the mainstream bank (and are low risk). In both of these situations, we expect such individuals to be the least likely to be assigned to a training program, due to a potential undermining effect on motivation (for high-risk individuals) or to their good performance ruling out any need for business training (for low-risk individuals). $\hat{\rho}_1$ is significant at 5%, suggesting that endogeneity bias is indeed an issue and the bivariate model is better able to deal with it than the univariate model.

Turning to the default equation, business training does not significantly impact the likelihood of defaulting. Male clients are significantly more likely to default than female clients. Higher education (measured by the number of qualifications achieved) significantly decreases a client's riskiness. Single individuals are more likely to default. Household income and expenses are respectively strong negative and positive determinants of the likelihood of defaulting. Borrowers with low personal investment seem to be riskier than businesses with greater assets. Businesses in the food and accommodation sector are riskier than those in other sectors of activity. Finally, the gross margin-to-sales ratio is associated with lower business risk.

Interestingly, rates of increase in business failures and start-ups are both positively correlated with risk. An increase in the rate of new business start-ups implies increasing competition in the sector, which will negatively impact the performance of the MFI's clients. An increase in failure rates is significant and positive one quarter after the beginning of the loan, whereas an increase in start-up rates is significant and positive at the time loan is granted. Overall, the signs of the loadings are in line with economic intuition.

Concerning heteroscedasticity, the indirect effects of business training and education are significant at 5% and 10% levels respectively, with opposite signs. A higher level of business training increases uncertainty about the risk of default. This would appear to be in line with the intuition that business training mainly targets "intermediary-risk" individuals. Finally, a higher level of education significantly decreases the variance of the unobserved individual heterogeneity term, v_i. In other words, there is more certainty about the risk of default for borrowers with higher education.

In the next section, several robustness checks are applied to our main results on the looking-glass self effect. We perform two robustness checks that consist in controlling for selection bias and defining an alternative measure of risk.

7 Robustness checks

7.1 Correcting for selection bias

In this section we add to the previous bivariate models a third equation, namely the loan approval decision, which allows us to correct for selection bias. Adding the approval process will also reveal whether the MFI chooses its clients optimally in terms of their expected performance, or if it accepts applicants regardless of their characteristics. This loan approval process is addressed in a reduced form: we do not impose any constraint on the link between the two equations. Instead, we add a third equation on loan approval, using the same explanatory variables w_i as in default equation, as suggested by Roszbach (2004):

$$y_{0i}^{*} = \beta_0 w_i^{'} + \eta_0 \mathbf{B_0}_i + \epsilon_{0i} \qquad y_{0i} = \begin{cases} 1 \quad if \quad y_{0i}^{*} > 0 \quad Granted \\ \\ 0 \quad if \quad y_{0i}^{*} \leq 0 \quad Otherwise \end{cases} \tag{6}$$

We moreover introduce into the approval equation business cycle variables ($\mathbf{B_0}_i$) that may impact the MFI's decision to grant the loan or not. $\mathbf{B_0}_i$ corresponds to the rate of increase in business failures and new business start-ups in the sector of enterprise i at the time of approval, and one quarter and two quarters before loan approval. The business cycles operating before approval of the loan will ensure the identification of the trivariate model.[21] In this model, we allow for correlation between both decisions (approval and business training) and the risk equation by imposing a similar structure on the error terms having an equivalent error composition and the same distributional assumptions:

$$\epsilon_{0i} \quad = \quad \rho_0 \upsilon_i + \epsilon_{0i}^{0}$$

The results are presented in Table 4.

[21]In the default equation business cycles are introduced at the beginning of the loan (and one and two quarters latter), whereas in the approval equation, business cycles are introduced at approval, which does not necessarily coincide with the beginning of the loan. Hence, it is possible for there to be no overlap between the business cycle variables in the approval and default equations.

Table 4: Determinants of Approval, Business Training and Default Processes

Model	Trivariate probit					
	(1)		(2)		(3)	
Dependent variable:	Approval		Business training		Default	
Explanatory variables:						
Risk			27.04***	(10.47)		
$Risk^2$			-46.13**	(20.93)		
Other applications			3.17***	(1.2)		
Honor loan			1.44***	(0.48)		
Sent by a mainstream bank			-1.5***	(0.53)		
$\hat{\rho}_1$			1.13**	(0.46)		
Business training (direct effect)					0.82***	(0.22)
Male	-0.16	(0.13)			0.51***	(0.13)
Education (direct effect)	-0.02	(0.05)			-0.27***	(0.07)
Single	-0.003	(0.14)			0.30**	(0.14)
Unemployed at least 12 months	-0.33**	(0.13)			0.13	(0.12)
Household income (kEUR)	0.12*	(0.07)			-0.46***	(0.07)
Household expenses (kEUR)	-0.24*	(0.14)			1.17***	(0.13)
Low personal investment	-0.31**	(0.14)			0.27**	(0.12)
Assets	0.003	(0.003)			-0.02***	(0.01)
Food and accommodation sector	-0.45**	(0.19)			0.67***	(0.18)
Gross margin/Sales	-0.57*	(0.32)			-0.28	(0.30)
$\hat{\rho}_0$	0.74***	(0.22)				
Rate of increase in failure approval stage	-2.93***	(0.79)				
Rate of increase in failure approval stage -1Q	-2.32***	(0.72)				
Rate of increase in start-ups beginning of loan					0.03***	(0.01)
Business training (indirect effect)					-14.17	(530)
Education (indirect effect)					0.32***	(0.09)
Intercept	0.77**	(0.34)	-3.67***	(1.42)	-1.38***	(0.32)
-2 Log Likelihood	1518					
Observations	662					

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

Only significant control variables for business cycles are presented.

Controlling for selection bias does not alter our main results. We note that the loadings for $Risk$ and $Risk^2$ are larger in absolute value compared to the bivariate model. The $Risk$ threshold at which the likelihood of receiving business training is reversed is 0.29. 11% of accepted borrowers have an estimated risk higher than 0.29.

As expected, the main coefficients in the approval equation are of the opposite sign to that in the risk equation. However, the estimates of some parameters change, the most striking difference being the direct effect of business training. Here, business training is found to increase the likelihood of defaulting, whereas in the bivariate model this coefficient was not significant. Interestingly, in the scedastic function, the indirect effect of business training is no longer significant and the indirect effect of education becomes significantly positive, suggesting that default risk uncertainty increases for better educated individuals.

Concerning business cycles, we note that the rate of increase in failures negatively impacts the approval process, whereas a higher rate of increase in start-ups at the beginning of the loan (*i.e.* greater competition) positively impacts the likelihood of defaulting.

Finally, both $\hat{\rho}_1$ and $\hat{\rho}_0$ are significant, suggesting that, there indeed is a correlation among the error terms of the three processes that has to be taken into account.

7.2 An alternative measure of risk: the inverse of survival time

One potential problem of our data is that borrowers receive microcredits at different times. Obviously, long-standing clients are more likely to default than to newly-granted loans. To get round the problem of censored data, we will use as a robustness check an alternative measure of risk consisting in the inverse of expected survival time. We fully expect this richer information to provide a clearer picture of the true default process. However, we cannot claim that this longitudinal approach will allow us to better replicate the assessment of borrowers' type by the MFI. Put another way, we do not know whether the MFI is able to use this more sophisticated measure of risk based on longitudinal assessment, or whether it ignores this information and only bases its decision on a simpler probit scoring model. Table 5 presents descriptive statistics on the survival time of each microcredit.

Table 5: Descriptive statistics for survival time (in days)

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

This extends the previous model by adding information on the survival time of a loan, T_i. In this model, the risk equation covers the time that elapses before a default occurs rather than just the occurrence of a default. We define t_i as follows. For defaulted loans, t_i is the number of days between the date the loan is granted and the date default occurs. For non-defaulted loans, t_i is the number of days between the date the loan is granted and the date of data extraction. The survival time is then either perfectly observed when a default occurs $y_{2i} = 1$, *i.e.* $T_i = t_i$, or is censored as the loan is still performing when $y_{2i} = 0$, *i.e.* $T_i > t_i$. The bivariate mixed model will allow us to estimate the survival time for each loan. To do so, we assume that survival time follows the Weibull distribution, the duration distribution most commonly used in applied econometrics (Lancaster 1992).

$$Ti|v_i, w_i, \mathbf{B}_i, y_{1i} \sim Weibull(\mu_i, \sigma) \qquad \text{where } \mu_i \equiv exp(\beta_2 w_i^{'} + \eta \mathbf{B}_i + \alpha_1 y_{1i} + \rho_{2i} v_i)$$

where $\rho_{2i} \equiv exp(\alpha_2 y_{1i} + \delta Education_i)$. The expected survival time is given by:

$$\mathbb{E}(T_i|w_i, \mathbf{B}_i, y_{1i}, v_i) = \mu_i^{-1}\Gamma(1 + \frac{1}{\sigma}) \tag{7}$$

where $\Gamma(.)$ is the complete Gamma function (for more details see Lancaster (1992), Appendix 1) and σ is the Weibull scale parameter. Consequently, the likelihood of default is necessarily inversely related to the expected survival time. We consider an alternative measure of this risk given by the inverse of $\mathbb{E}(T_i|w_i, v_i)$. We therefore replace the probability of defaulting by this alternative measure of risk in the business training decision process. Consistent with previous models, we obviously exclude both the current decision y_{1i} and the business cycle variables from the set of covariates.

Concerning the identification strategy, the expected survival time of a loan will be identified using the observed survival time, censored or not, of the granted loans. The identification mechanism in this model, like the baseline model, is not only obtained through the non-linear function of the linear combination of the determinants of risk but, above all, by the inclusion of business cycle indicators in the duration model. We present the results of the estimation for this model in Table 6.

The non-monotonic relationship between y_2 and *Risk* is robust to the introduction of this alternative risk measure.[22] The threshold where business training becomes decreasing with risk is 1.78. Estimating risk, which is the inverse of survival time, for the MFI's clients, we find that only 2% of the sample has an expected risk higher than 1.78. Note however, that despite giving a better estimation of the real default process, the mixed model does not necessarily provide a better proxy of the information available to the MFI in practice. Crucially, in this mixed model the coefficient for y_2 becomes significant in the inverse of the survival time equation. This finding suggests that business training is indeed useful to increase a business's chances of success. The non-significance of this coefficient in the bivariate probit equation might be due to reduced variability in the risk variable, which is a dummy. Nevertheless, the positive significant impact in the trivariate model leaves the current debate on the efficiency of business training open.

The Weibull parameter is significant and positive, suggesting that risk is increasing with time. The signs of other controls are in line with previous findings, despite some differences in significance: for example, long-term unemployment becomes highly significant.

[22] We multiply the *Risk* variable by 100 to scale down the estimated coefficients and render them comparable to other loadings.

Table 6: Determinants of Business Training and Inverse of Survival Time

Model	Bivariate Mixed			
	(1)		(2)	
Dependent variable:	Business training		Inverse of Survival Time	
Explanatory variables:				
Risk	1.71***	(0.65)		
Risk^2	-0.48**	(0.22)		
Other applications	1.15***	(0.19)		
Honor loan	0.56***	(0.18)		
Sent by a mainstream bank	-0.53***	(0.2)		
$\hat{\rho}_1$	0.23	(0.17)		
Business training (direct effect)			-0.86***	(0.23)
Male			0.67***	(0.22)
Education (direct effect)			-0.49***	(0.1)
Single			-0.16	(0.14)
Unemployed at least 12 months			0.53***	(0.14)
Household income (kEUR)			-0.41***	(0.09)
Household expenses (kEUR)			0.8***	(0.18)
Low personal investment			0.48***	(0.14)
Assets			-0.01	(0.01)
Food and accommodation sector			0.06	(0.21)
Gross margin/Sales			-1.16***	(0.31)
Business training (indirect effect)			-0.22	(0.14)
Education (indirect effect)			0.13***	(0.05)
Rate of increase in failures beginning of loan			0.006	(0.004)
Rate of increase in failures beginning of loan +1Q			0.01**	(0.004)
Rate of increase in failures beginning of loan +2Q			0.01***	(0.003)
Rate of increase in start-ups beginning of loan			0.005*	(0.003)
Rate of increase in start-ups beginning of loan +1Q			0.001	(0.003)
Rate of increase in start-ups beginning of loan +2Q			-0.01***	(0.003)
Weibull parameter			3.02***	(0.55)
Intercept	-0.96***	(0.19)	-5.57***	(0.36)
-2 Log Likelihood	1612			
Observations	340			

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

8 Conclusion

In this paper we analyze how superior information can impact MFIs' decisions to assign borrowers to training programs. In the theoretical model we show that, in situations where the relationship between business training and borrower type is decreasing under symmetric information, a non-monotonic relationship between business training and borrower type may arise under reversed asymmetric information, where the MFI has superior information about the borrower's type.

We reveal the existence of this equilibrium using original data from a French MFI which, in addition to loan-granting, assigned some of its clients to training programs. Using a bivariate probit model to control for endogeneity between business training and the riskiness of the borrower, we show that a non-monotonic relationship between assignment to training and the risk of default is indeed observed in practice. The MFI seems to take into account the "looking-glass self effect", that is the fact that its choices impact borrowers' beliefs about their type on the microcredit market.

Our paper provides interesting insights into how MFIs' decisions might undermine borrowers' motivation to exert effort. However, further research would contribute evidence to support the conditions on borrowers' beliefs in this mechanism. It would be useful to confirm the assumptions of the theoretical model by testing the hypothesis that business training has a greater impact on high-risk borrowers than on low-risk borrowers.

9 Appendix

A. Bivariate Probit Model: Likelihood Function

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

$$Li(\theta|y_{1i},y_{2i},x_i,w_i,v_i) = \underbrace{\Phi\left(x_i^{'}\beta_1 + \lambda_1\Phi(w_i^{'}\beta_2+v_i) + \lambda_2\left[\Phi(w_i^{'}\beta_2+v_i)\right]^2 + \rho_1 v_i\right)^{y_{1i}}}_{P(y_{1i}=1|v_i,\ldots)} \cdot$$
$$\underbrace{\left[1-\Phi\left(x_i^{'}\beta_1 + \lambda_1\Phi(w_i^{'}\beta_2+v_i) + \lambda_2\left[\Phi(w_i^{'}\beta_2+v_i)\right]^2 + \rho_1 v_i\right)\right]^{(1-y_{1i})}}_{P(y_{1i}=0|v_i,\ldots)} \cdot$$
$$\underbrace{\left[\Phi(w_i^{'}\beta_2 + \eta\mathbf{B}_i + \alpha_1 y_{1i} + v_i)\right]^{y_{2i}}}_{P(y_{2i}=1|v_i,y_{1i},\ldots)} \cdot \underbrace{\left[1-\Phi(w_i^{'}\beta_2 + \eta\mathbf{B}_i + \alpha_1 y_{1i} + v_i)\right]^{(1-y_{2i})}}_{P(y_{2i}=0|v_i,y_{1i},\ldots)}$$

Hence, in the first model with two simultaneous probit equations we 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.

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

B. Trivariate Probit Model: Likelihood Function

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

$$Li(\theta|y_{0i},y_{1i},y_{2i},w_i,x_i,v_i) = \underbrace{\Phi\left(w_i^{'}\beta_0 + \eta_{\mathbf{0}}\mathbf{B}_{0i} + \rho_0 v_i\right)^{y_{0i}}}_{P(y_{0i}=1|v_i,\ldots)} \cdot \underbrace{\left[1-\Phi\left(w_i^{'}\beta_0 + \eta_{\mathbf{0}}\mathbf{B}_{0i} + \rho_0 v_i\right)\right]^{(1-y_{0i})}}_{P(y_{0i}=0|v_i,\ldots)} \cdot$$
$$\underbrace{\Phi\left(x_i^{'}\beta_1 + \lambda_1\Phi(w_i^{'}\beta_2+v_i) + \lambda_2\left[\Phi(w_i^{'}\beta_2+v_i)\right]^2 + \rho_1 v_i\right)^{y_{0i}y_{1i}}}_{P(y_{1i}=1|v_i,y_{0i}=1,\ldots)} \cdot$$
$$\underbrace{\left[1-\Phi\left(x_i^{'}\beta_1 + \lambda_1\Phi(w_i^{'}\beta_2+v_i) + \lambda_2\left[\Phi(w_i^{'}\beta_2+v_i)\right]^2 + \rho_1 v_i\right)\right]^{y_{0i}(1-y_{1i})}}_{P(y_{1i}=0|v_i,y_{0i}=1,\ldots)} \cdot$$
$$\underbrace{\left[\Phi(w_i^{'}\beta_2 + \eta\mathbf{B}_i + \alpha_1 y_{1i} + v_i)\right]^{y_{0i}y_{2i}}}_{P(y_{2i}=1|v_i,y_{0i}=1,y_{1i},\ldots)} \cdot \underbrace{\left[1-\Phi(w_i^{'}\beta_2 + \eta\mathbf{B}_i + \alpha_1 y_{1i} + v_i)\right]^{y_{0i}(1-y_{2i})}}_{P(y_{2i}=0|v_i,y_{0i}=1,y_{1i},\ldots)}$$

Hence, in the model with three simultaneous probit equations we 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.

$$
\begin{aligned}
& l(\theta | y_{0i}, y_{1i}, y_{2i}, w_i, x_i) \\
= \quad & \sum_{i=1}^{n} \ln \left(\int Li(\theta | y_{0i}, y_{1i}, y_{2i}, w_i, x_i, v_i) \phi(v_i) dv_i \right)
\end{aligned}
$$

C. Bivariate Mixed Model: Likelihood Function

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

$$
\begin{aligned}
& Li(\theta | y_{1i}, y_{2i}, t_i, x_i, w_i, v_i) \\
= \quad & \underbrace{\Phi \left(x_i^{'} \beta_1 + \lambda_1 E(T_i)^{-1} + \lambda_2 E(T_i)^{-2} + \rho_1 v_i \right)^{y_{1i}}}_{P(y_{1i}=1|v_i,...)} \\
& \underbrace{\left[1 - \Phi \left(x_i^{'} \beta_1 + \lambda_1 E(T_i)^{-1} + \lambda_2 E(T_i)^{-2} + \rho_1 v_i \right) \right]^{(1-y_{1i})}}_{P(y_{1i}=0|v_i,...)} \\
& \underbrace{\left[\sigma \mu_i^{\sigma} t_i^{\sigma-1} exp \left\{ - (\mu_i t_i)^{\sigma} \right\} \right]^{y_{2i}}}_{f(t_i|v_i,y_{1i},...)} \underbrace{\left[exp \left\{ - (\mu_i t_i)^{\sigma} \right\} \right]^{(1-y_{2i})}}_{P(T_i>t_i|v_i,y_{1i},...)}
\end{aligned}
$$

D. Univariate Model Results

Table 7: Determinants of Business Training and Default Processes

Model	Univariate probit			
	(1)		(2)	
Dependent variable:	Business training		Default	
Explanatory variables:				
Risk	1.07	(1.4)		
Risk^2	-1.20	(2.4)		
Other applications	1.07***	(0.17)		
Honor loan	0.51***	(0.16)		
Sent by a mainstream bank	-0.55***	(0.19)		
$\hat{\rho}_1$				
Business training (direct effect)			-0.15	(0.18)
Male			0.62***	(0.2)
Education (direct effect)			-0.18**	(0.07)
Single			0.06	(0.19)
Unemployed at least 12 months			0.33*	(0.19)
Household income (kEUR)			-0.29**	(0.12)
Household expenses (kEUR)			0.66***	(0.23)
Low personal investment			0.35*	(0.19)
Assets			-0.02***	(0.01)
Food and accommodation sector			0.23	(0.31)
Gross margin/Sales			-1.03**	(0.45)
Rate of increase in failures beginning of loan			0.009	(0.006)
Rate of increase in failures beginning of loan +1			0.008*	(0.004)
Rate of increase in failures beginning of loan +2			0.007	(0.005)
Rate of increase in start-ups beginning of loan			0.012***	(0.004)
Rate of increase in start-ups beginning of loan +1			0.006	(0.004)
Rate of increase in start-ups beginning of loan +2			-0.001	(0.004)
Intercept	-0.75***	(0.22)	-0.03	(0.48)
-2 Log Likelihood	371		293	
Observations	342		340	

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

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