

Business Training and Loan Repayment: Theory and Evidence from Microcredit in France

Renaud Bourlès
Anastasia Cozarenco
Dominique Henriët
Xavier Joutard

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Renaud Bourlès^a

Anastasia Cozarenco^{b2}

Dominique Henriët^a

Xavier Joutard^c

^aAix-Marseille University, CNRS, EHESS, Centrale Marseille, AMSE

^bMontpellier Business School, Montpellier Research in Management, and Centre for European
Research in Micronance (CERMi)

^cAix-Marseille University, CNRS, LEST and OFCE

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²Corresponding author. Address: Montpellier Business School, 2300, avenue des Moulins, 34185, Montpellier cedex 4; Email: a.cozarenco@montpellier-bs.com, Phone: +33.4.67.10.26.35.

Abstract

Although most Microfinance Institutions (MFIs) invest in non-financial services such as business training, empirical evidence on the impact of training on microborrowers' performance is at best mixed. We address this issue by accounting for business training allocation and its possible effects on borrowers' behavior. We first show empirically (using data from a French MFI) that the relationship between business training allocation and borrowers' risk is complex and non-linear. By taking this into account, we establish a positive effect of business training on the survival time of loans. These results are robust to controlling for the MFI's selection process. We moreover propose a theoretical explanation for the non-linear relationship between borrowers' risk and training allocation based on reverse asymmetric information, showing that it can lead to increased MFI outreach.

Keywords: microcredit, business training, reverse asymmetric information

JEL Codes: C34, C41, D82, G21

1 Introduction

Microfinance clients are individuals rejected by conventional banks due to their lack of collateral, credit history or experience of starting a business. Non-financial services play an important role in the microfinance sector: combined with financial services, they contribute to the alleviation of human capital constraints (Schreiner and Morduch, 2002) through a maximalist (versus minimalist) approach. Non-financial services take various forms, such as financial literacy (Sayinzoga et al., 2016), information about health and human rights, money management, and business training.

European Microfinance Institutions (MFIs) have been involved in business training since their emergence (Lammermann et al., 2007). Business training consists of entrepreneurial training or business development services that generally accompany business microloans, like guiding the definition and development of the business project, providing information and help with obtaining financing, offering courses in accounting, management, marketing and law, etc. Armendariz (2009) refers to “guided” microcredit to describe the main product provided by European MFIs. In France, the National Council for Statistical Information includes business support services in the definition of microcredit (Valentin et al., 2011). According to Botti et al. (2016), 58% of surveyed European MFIs provide non-financial services to their clients.

Yet although business training is a recognized component of microfinance, existing evidence on its impact is mixed at best. There are at least two potential reasons for this. First, some studies examine samples that may not be representative of the general population (McKenzie and Woodruff, 2013). Second, even though recent studies have overcome the selection bias by using randomized controlled trials, they do not account for behavioral reactions that assignment to business training may trigger among participants. The failure to consider borrowers’ behavioral reactions, as well as the rationale behind assignment to training, is thus likely to bias results on the impact of business training.

Here, using data from a French MFI, we investigate the effect of business training on loan repayment, controlling for the process of assignment to training in bivariate probit and mixed (duration) models. First, we show that business training allocation is complex and that the relationship between borrowers' risk and assignment to business training is non-linear. More specifically, we find that the probability of being assigned to business training first increases with borrowers' risk, and then, beyond a certain threshold, decreases. Second, controlling for this non-linear effect, we find a positive impact of business training on loan survival time. This result is robust to correcting for potential selection bias (Heckman, 1979) during the MFI's credit approval stage.

To rationalize the non-linear effect of borrowers' risk on training allocation, we build a theoretical model based on the mechanisms of reverse asymmetric information, i.e. on the assumption that the MFI has better information on risk than the borrowers themselves. This assumption is plausible in contexts where MFIs are financing first-time micro-entrepreneurs who need financial backing to start a business, and who usually lack the necessary experience. In this case, the contract offered by the MFI (assignment to training or not)³ reveals to the borrowers information about themselves, thereby impacting their actions. This "looking-glass self" mechanism was introduced by Cooley (1902); to the best of our knowledge, our study is the first to introduce the concept in microfinance. Using a simple discrete model, we show that reverse asymmetric information can indeed generate non-linearity between borrowers' risk and assignment to business training. Moreover, we argue that in such a theoretical setting, reverse asymmetric information is likely to increase outreach to riskier borrowers, which is the ultimate goal of MFIs striving to mitigate financial exclusion.

The remainder of the paper is structured as follows. In section 2 we review the extant literature.

We present the institution providing data and the dataset in section 3. The econometric strategy is

³In the microfinance context where loans are not collateralized and interest rates are fixed, MFIs generally tailor loan size to the applicant's expected creditworthiness (Agier and Szafarz, 2013). However, the MFI in our study is constrained by a French regulatory loan ceiling (Cozarenco and Szafarz, 2016), reducing the opportunity for loan size tailoring. Therefore, in our case, assignment to training is the main source of contract heterogeneity.

described in section 4 and the empirical results are outlined in section 5. We check the robustness of our results in section 6. A theoretical model rationalizing the intuition behind our empirical results is presented in section 7. Section 8 concludes.

2 Literature review

Our study contributes to three strands of the literature: (i) the impact of training programs in microfinance; (ii) the empirics of bivariate and trivariate probit and duration models (which can also be interpreted as scoring models in banking); and (iii) the theoretical effect of reverse asymmetric information.

The extant literature is agnostic about the efficiency of business training in microfinance. For instance, [Evans \(2011\)](#) underlines some positive outcomes for business training under the Women's Initiative for Self Employment, whereas [Edgcomb \(2002\)](#) reports mixed results on correlations between completed training and successful entrepreneurship outcomes in the United States. However, these studies ignore the non-random allocation of business training and the selection bias this may induce.

More recent studies adopt an experimental approach using random business training allocation. For developing countries, for instance, [Karlan and Valdivia \(2011\)](#) 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.⁴ [Berge et al. \(2014\)](#) argue that business training combined with financial services improves business outcomes for male microentrepreneurs in Tanzania (the effects for women being non-significant). [Bulte et al. \(2014\)](#) find considerable impacts on knowledge, business practices and outcomes for female clients of an MFI in Vietnam; however these impacts take time to materialize.

⁴See [McKenzie and Woodruff \(2013\)](#) for an extended review of existing studies of impacts of business training in developing countries.

For developed countries, the evidence is scarce, with two welcome exceptions. [Fairlie et al. \(2015\)](#) find no long-lasting effects of business training in the United States for individuals who are potentially subject either to credit or human capital constraints or to discrimination in the labor market. Similarly, the randomized controlled trial conducted by [Crépon et al. \(2014\)](#) with ADIE (the largest French MFI) did not identify significant positive impacts in terms of business outcomes for participants.

Beyond business outcomes, few studies have focused on the relationship between business training and credit repayment.⁵ One exception is [Karlan and Valdivia \(2011\)](#), who find that access to training increases the probability of perfect repayment to the MFI; however, this result is only marginally significant. Similarly, [Giné and Mansuri \(2014\)](#) find that training has no significant impact on repayment rates for microfinance clients in rural Pakistan.

Unfortunately, we do not have data on business outcomes for borrowers in our study. However, we have access to detailed individual data on credit repayment history within the MFI. Therefore our main focus is the relationship between business training and credit repayment. Taking into account the behavioral aspects of assignment to business training ([Benabou and Tirole, 2003a](#)), we find a non-significant impact of business training on the probability of default, but a significant positive impact on loan survival time.

Our empirical strategy is based on bivariate models where we jointly estimate two equations. The first equation models the business training allocation process, whereas the second equation models borrowers' risk. We first measure borrowers' risk using probability of default in a bivariate probit model. A comparable bivariate probit model was developed by [Boyes et al. \(1989\)](#), where the two probit equations concern the loan granting process and borrowers' default respectively. However, the empirical literature argues that despite defaults, some loans may still be profitable if the default

⁵There are two main reasons for this. First, some of the studies focus on the impact of business training for beneficiaries who are not necessarily microcredit recipients. Second, repayment rates are very high in microfinance in developing countries ([Armendariz and Morduch, 2010](#)), so there is little heterogeneity in terms of credit 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 bivariate survival time model. In line with this study, we use loan survival time as an alternative measure of risk in a bivariate mixed (duration) model.

Econometric models in [Boyes et al. \(1989\)](#) and [Roszbach \(2004\)](#) are examples of credit scoring models underlining the importance of controlling for banks' selection process during the approval stage ([Heckman, 1979](#)). To address selection bias, our paper pioneers the development of trivariate probit and mixed models to test for robustness of results, by adding a selection equation to our bivariate models.

We take advantage of the risk equation to estimate borrowers' intrinsic risk. First, we study the relationship between business training allocation and borrowers' intrinsic risk, which appears to be non-linear. Second, we take into account this complex relationship to study the impact of business training on loan repayment. The original feature of our paper lies in the development of formal empirical models addressing the endogeneity of business training allocation and its consequences.

Our theoretical modeling explaining the non-linear relationship between risk and training assignment is based on reverse asymmetric information (where the principal is better informed than the agent) and the looking-glass self effect. The latter occurs when people in their social environment attempt to manipulate self-perception. This phenomenon has been widely studied in the sociological literature. The term "looking-glass self" was coined 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.⁶

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 an 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. Crucially, these authors point out that their model only fits situations where agents are at the beginning of their career or are performing tasks for the first time, whereas the principal has previous experience with similar tasks or agents. This setting is remarkably similar to the microcredit market, where micro-entrepreneurs are borrowing from an experienced MFI to start a business for the first time. One contribution of this paper is to introduce the notion of informed principal and the looking-glass self effect to the credit market.

3 Context and Data

3.1 Institutional context of the MFI

Créa-Sol, 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 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,

⁶Other 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.

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 that the total pool of applicants of this MFI is considered "too risky" by most commercial banks. The MFI provides both personal and business microcredit. We focus on business microcredit exclusively.

In addition to microcredit services, Créa-Sol is highly active in business training provision. Non-financial services are an important feature of MFIs in France, which play a counseling and support role (Brana, 2013) and use soft information in their screening processes (Cozarenco and Szafarz, 2018). Providing business training is costly for MFIs, so they cut costs by forming partnerships with NGOs.⁷

We have information on all the applicants who were granted a microcredit by our MFI between May 2008 and May 2011, as well as on any accompanying business training provision. To our knowledge, the MFI's borrowers did not receive any training other than that mentioned in the 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 chooses primarily to train riskier clients. Unfortunately, we do not have data on business outcomes (ex. profits, sales, etc.), only business forecasts from the application stage via a business plan presented by the applicant. Hence, we cannot investigate the link between business training provision and business outcomes. However, our data set contains detailed information on borrowers' behavior regarding ex-post repayment to the MFI. We use the number and dates of unpaid installments to explore the impact of business training on loan repayment.

Each individual can apply only once for a microcredit. Our MFI aims to have all its clients bankable

⁷According to Botti et al. (2016), 87% of Western European MFIs providing non-financial services externalized them to third-parties.

after their first microcredit.⁸ The relationship between the MFI and the borrower proceeds as follows. After receiving a credit application, the MFI decides whether to accept or reject the loan. 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 to provide training to the selected applicants.⁹ Training is mandatory for the selected borrowers, who cannot refuse to participate. We then observe each client’s microcredit repayment behavior, i.e. the number and dates of unpaid installments.

3.2 Data

Using Créa-Sol’s data, we model two different processes:

1. Business training allocation
2. Borrower’s risk based on his/her credit history

Table 1 gives the descriptive statistics for our data along with the t-tests to compare different group means. Information on 365 business microcredit borrowers was collected between May 2008 and May 2011.¹⁰ The vast majority of these loans were for a business start-up or buy-out, rather than for business development. The average loan approved was EUR 8,900, the average interest rate was 4.2%¹¹ and the mean maturity was 52 months.

Column (1) in Table 1 lists 22% of the borrowers as defaulting. We define as “defaulting” borrowers with 3 or more delayed payments in their credit history within the MFI.¹² The delayed payments

⁸As a consequence, the MFI does not provide dynamic incentives through progressive lending.

⁹We cannot completely rule out the possibility that loan granting and training assignment processes are not strictly sequential or intertwined. We account for this eventuality in a robustness check using a nested logit model.

¹⁰We do not study consumer loans, in contrast to Roszbach (2004).

¹¹The 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.

¹²This percentage might appear particularly high in the microfinance context. Indeed, D’Espallier et al. (2011) report 6% of the total loan portfolio as more than 30 days overdue, and only 1% of loans as written-off in a study of 350 MFIs in 70 countries. However, for MFIs in Western Europe the percentage of the total loan portfolio overdue more than 30 days is 13.4% and the write-off ratio is 5.6% according to Botti et al. (2016), comparable with the figures reported in our study.

Table 1: Descriptive Statistics

Variables	Total (1)	Training (2)	No Training (3)	t-test ^a (4)	Defaulting (5)	Performing (6)	t-test (7)
Defaulting (dummy)	0.22	0.19	0.25	-0.05			
Business training (dummy)	0.55				0.49	0.57	-0.08
Individual Characteristics							
Male (dummy)	0.61	0.62	0.60	0.02	0.75	0.58	0.17***
Education (no. of diplomas)	1.89	1.89	1.89	0.00	1.46	2.01	-0.55***
Single (dummy)	0.53	0.50	0.57	-0.07	0.63	0.51	0.13**
Unemployed more than 12 months (dummy)	0.33	0.37	0.28	0.08*	0.42	0.31	0.11*
Household Characteristics							
Household income (kEUR)	1.49	1.61	1.33	0.29**	1.11	1.59	-0.49***
Household expenses (kEUR)	0.45	0.47	0.42	0.06	0.47	0.44	0.03
Business Characteristics							
Low personal investment (dummy)	0.26	0.25	0.27	-0.02	0.38	0.23	0.15***
Assets (kEUR)	18.86	21.34	15.73	5.62**	12.19	20.74	-8.55***
Food and accommodation sector (dummy)	0.10	0.08	0.13	-0.04	0.09	0.11	-0.02
Gross margin(EUR)/Sales(EUR)	0.74	0.74	0.74	0.00	0.71	0.75	-0.03
Instruments for business training process							
Other applications (dummy)	0.62	0.82	0.38	0.44***			
Honor loan (dummy)	0.47	0.63	0.28	0.36***			
Sent by a mainstream bank (dummy)	0.18	0.12	0.26	-0.14***			
No. of observations	365	202	163		79	286	

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

^aThe t-test is a two-sample two-sided test for equal means.

need not be consecutive or remain unpaid, although most delayed payments in the database were consecutive. This definition mirrors the MFI's actual policy: it generally writes off all loans involving three or more consecutive delayed payments. However, our definition is more conservative and results in a larger percentage of defaulting loans than was actually registered by the MFI.

In columns (2) and (3) of Table 1 we split the total sample into business training beneficiaries and non-beneficiaries respectively. 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. Importantly, these preliminary descriptive statistics suggest that individuals assigned to training are not riskier ex-post than individuals without training. 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. As pointed out above, studies in both developed and developing economies fail to corroborate the first scenario, where business training is highly efficient. This lends credence to the second scenario,

where business training is not necessarily allocated to the riskier borrowers.

Overall, 55% of the borrowers were assigned to business training.¹³ In columns (5) and (6) we split the sample into defaulting and performing loans (loans that have strictly less than three delayed payments in their credit history). Almost half the defaulting loans versus 57% of performing loans were assigned to a training program, but this difference is not significant either.

The individual characteristics of business training beneficiaries and of non-beneficiaries do not appear to differ much. Nevertheless, a few differences deserve mention. The proportion of long-term unemployed individuals is greater among borrowers assigned to business training. Moreover, business training beneficiaries have higher household incomes and their businesses have higher asset levels.

Furthermore, they are more likely to have made other applications and to have been granted honor loans,¹⁴ which is consistent with a microcredit setup where NGOs providing training programs in partnership with MFIs 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, borrowers sent by a mainstream bank are less likely to be assigned to a training program. Borrowers sent by a mainstream bank either have a co-financing loan from the bank (these are potentially less risky clients) or have been rejected by the bank (these are potentially riskier clients).

These descriptive statistics suggest that the relationship between borrowers' risk and training allocation is complex and potentially non-linear. Therefore it is important to account for this effect

¹³Assignment 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.

¹⁴An 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.

when assessing the effect of business training on loan repayment. For the reasons outlined above, we use the variables *Other applications*, *Honor loan*, *Sent by a mainstream bank* as instruments in the business training allocation process to identify our effects.

As Table 1 illustrates, there are significant differences between defaulting and performing clients. Defaulting clients are more likely to be male, single, and long-term unemployed, with lower education, income levels, personal investment¹⁵ and assets. All these variables are taken into account to design our risk measure, or a borrower's score. Actually, we do not have information on the scoring model used by the MFI. Therefore we use *ex-post* information on credit history to estimate the borrower's *ex-ante* risk, assuming that the MFI's scoring strategy is based on its previous experience. This risk measure will allow us to model business training assignment and, consequently, to establish a positive effect of business training on credit repayment. Our econometric strategy is outlined in the next section.

4 Econometric model

The purpose of our paper is to study the effect of business training on microcredit repayment. To address this issue, we need to control for assignment to business training. We proceed as follows. First, we construct a measure of borrowers' (intrinsic) risk, or score, using the loan repayment equation. Second, we introduce this measure of borrowers' risk (first linearly and then quadratically) into the business training allocation equation. By simultaneously estimating the two equations, we show that this relationship is non-linear and, at the same time, we establish a positive effect of business training on loan survival time.

To proxy borrowers' risk, we first use a probit equation that estimates the probability of a borrower

¹⁵Low 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.

defaulting in a bivariate probit model. Alternatively, we use the inverse of loan survival time in a bivariate mixed model. Among the control variables, we include individual, household and business characteristics presented in Table 1. In addition, we control for business cycles,¹⁶ which obviously impact the riskiness of a project: 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 is granted (and one and two quarters later) for each micro-enterprise in our sample, according to its sector of activity. Data for business cycles exclusively cover the French Southeastern PACA Region where our MFI operates.

Furthermore, loan repayment potentially depends on business training, both directly and indirectly through borrowers' behavioral reactions to business training assignment. We attempt to isolate these two effects. To identify the direct effect of business training, we introduce into the risk equation an additional covariate, the *Business training* dummy, taking value one if a borrower receives business training and zero otherwise. To isolate behavioral effects, we also introduce into the risk equation a form of heteroscedasticity linked to individual unobserved heterogeneity and depending on, among others, business training.

This approach allows us to estimate the variable *Risk* depending solely on individual, household, and business characteristics to proxy borrowers' intrinsic risk (i.e. the risk net of potential direct and indirect effects of business training and net of business cycle influence). We test the following hypotheses:

H1: The intrinsic risk of a borrower impacts his/her probability of receiving business training.

H2: Business training positively impacts loan repayment when we control for the pro-

¹⁶Source: Fiben, Banque de France.

cess of assignment to business training and its possible behavioral effects.

To test H1, we first introduce variable *Risk* linearly and then quadratically (to capture the simplest form of non-linearity) in the business training allocation equation. H2 is tested by assessing the sign and the significance level of the *Business training* loading in the risk equation, as specified in the remainder of this section.

4.1 Bivariate probit model

To test the relationship between the probability of receiving business training and borrowers' risk, we add intrinsic risk to the business training equation. Actually, we jointly model two processes, namely the business training decision and the probability of defaulting, related by a common unobserved individual heterogeneity factor. This unobserved individual heterogeneity allows us to take into account the unobserved "soft" information about borrowers (motivation, skills, personality, etc.) collected by the MFI during face-to-face meetings. These factors drive the borrowers' behavior (for instance, through effort devoted to the business). In addition, joint modeling controls for the endogeneity of business training in the default equation.

Furthermore, the heteroscedasticity of the model captures the idea that observing the same level of business training can trigger different behavioral reactions in two different borrowers. In other words, assignment to business training could introduce noise into a borrower's behavior, thereby engendering noise in his/her probability of defaulting, which could imply higher and non-constant variance. This can naturally be represented by a scedastic function attached to the unobservable individual heterogeneity. By introducing heteroscedasticity into the default equation, we isolate behavioral effects on the probability of defaulting.

Thus, controlling for endogeneity and introducing heteroscedasticity help disentangle three different components in the risk equation: the direct effect of business training, the indirect effect of business training through borrower's behavior and the intrinsic risk of the borrower.

We first study a linear relationship between business training and *Risk* in Model I. Then, we consider the simplest form of non-linearity by introducing *Risk* and *Risk*² into the business training equation in Model II. The bivariate probit model consists of two simultaneous equations: the first for the binary decision to provide business training or not, y_{1i} ; and the second for the binary outcome defaulting or not, y_{2i} :

Model I:

$$y_{1i}^* = \beta_1 x_i' + \lambda_1 Risk + \epsilon_{1i}, \quad y_{1i} = \begin{cases} 1 & \text{if } y_{1i}^* > 0 \text{ Business training} \\ 0 & \text{if } y_{1i}^* \leq 0 \text{ Otherwise} \end{cases} \quad (1)$$

$$y_{2i}^* = \beta_2 w_i' + \eta \mathbf{B}_i + \alpha_1 y_{1i} + \epsilon_{2i}, \quad y_{2i} = \begin{cases} 1 & \text{if } y_{2i}^* > 0 \text{ Defaulting} \\ 0 & \text{if } y_{2i}^* \leq 0 \text{ Otherwise} \end{cases} \quad (2)$$

In **Model II** equation (1) writes

$$y_{1i}^* = \beta_1 x_i' + \lambda_1 Risk + \lambda_2 Risk^2 + \epsilon_{1i}, \quad y_{1i} = \begin{cases} 1 & \text{if } y_{1i}^* > 0 \text{ Business training} \\ 0 & \text{if } y_{1i}^* \leq 0 \text{ Otherwise} \end{cases} \quad (3)$$

and equation (2) remains unchanged.

x_i is a vector of variables specific to the business training decision including *Honor loan*, *Other applications* and *Sent by a mainstream bank*. As described in the Data section, these three variables are directly linked to the business training process and are used as instruments in this equation to ensure model identification.

w_i is a vector of various controls composed of individual, household and business characteristics. \mathbf{B}_i is a vector of variables measuring the business cycle of the sector of activity of enterprise i . They ensure full identification of our model since they cannot impact training, as they occur after assignment to training.

The correlation between the business training and defaulting processes is modeled by imposing the following

structure on the error terms:

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

where the components $\epsilon_{1i}^0, \epsilon_{2i}^0$ 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 is the individual unobserved heterogeneity factor. We assume that $v_i \sim \mathcal{N}(0, 1)$ and that this factor is independent of the idiosyncratic terms. Attached to v_i , the scedastic function $\rho_{2i} \equiv \rho_2 \exp(\alpha_2 y_{1i} + \delta \text{Education}_i)$ represents uncertainty driven by borrowers' behavioral effects: here, business training indirectly impacts the probability of defaulting through α_2 . We moreover assume that the behavioral effect 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, borrowers' intrinsic risk¹⁷ is proxied by $Risk = \Phi(w_i' \beta_2 + v_i)$, where $\Phi(\cdot)$ is the normal cumulative distribution function. We estimate the parameters using the maximum likelihood method (see Appendix 9.1 for details of the likelihood function).

If H1 is verified, we expect $\hat{\lambda}_1$ (resp. $\hat{\lambda}_1$ and $\hat{\lambda}_2$) to be significantly different from zero in Model I (resp. Model II). If H2 is verified, we expect $\hat{\alpha}_1$ to be significantly negative in equation (2). The results of the estimation of Models I and II are presented in Table 3 in the next section.

4.2 Bivariate mixed model

A characteristic of our data is that borrowers receive microcredits at different times and some microcredits are still active at the time of observation. Obviously, long-standing clients are more likely to default compared to newly-granted loans. Moreover, the time elapsed before delayed payments occur is observed. This longitudinal aspect of the data allows us to take into account a strong heterogeneity within defaulting loans. This richer information should provide a clearer picture of the true default process and a better

¹⁷By intrinsic risk we mean the probability of defaulting "cleaned" of the direct effect of business training, indirect behavioral effects and business cycle effects.

assessment of a borrower’s intrinsic risk. Importantly, as highlighted by [Roszbach \(2004\)](#), the impact of a default on an MFI’s returns (or a bank’s returns in his case) depends to a large extent on when (in the history of the loan) this default occurs.

However, we cannot claim that this longitudinal approach will allow us to better replicate the MFI’s assessment of borrowers’ intrinsic risk. 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 bases its decision solely on a simpler probit scoring model. [Table 2](#) presents descriptive statistics on the survival time of each microcredit.

Table 2: Descriptive statistics for survival time (in days)

Sub-sample	Mean	SD	Min	Percentiles							
				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 . We choose an alternative measure of risk consisting in the inverse of the expected survival time. In this model, the risk equation covers the time that elapses before a default occurs, rather than just the default. We define t_i as follows. For defaulting loans, t_i is the number of days between the date the loan is granted and the date default occurs. For non-defaulting loans, t_i is the number of days between the date the loan is granted and the date of data extraction. Either the survival time is perfectly observed when a default occurs $y_{2i} = 1$, i.e. $T_i = t_i$, or it is censored because the loan is still performing when $y_{2i} = 0$, i.e. $T_i > t_i$. The bivariate mixed model allows us to estimate survival time for each loan, assuming that survival time follows the Weibull distribution, the duration distribution most commonly used in applied econometrics ([Lancaster, 1992](#)).

$$(T_i | v_i, w_i, \mathbf{B}_i, y_{1i} \sim Weibull(\mu_i, \sigma)) \quad (4)$$

where $\mu_i \equiv \exp(\beta_2 w_i' + \eta \mathbf{B}_i + \alpha_1 y_{1i} + \rho_{2i} v_i)$ and $\rho_{2i} \equiv \exp(\alpha_2 y_{1i} + \delta Education_i)$.

The expected survival time is given by:

$$\mathbb{E}(T_i | w_i, \mathbf{B}_i, y_{1i}, v_i) = \mu_i^{-1} \Gamma \left(1 + \frac{1}{\sigma} \right) \quad (5)$$

where $\Gamma(\cdot)$ is the complete Gamma function (for more details see [Lancaster, 1992](#), Appendix 1) and σ is the Weibull scale parameter. Consequently, borrower's risk is necessarily inversely related to expected survival time. We consider an alternative measure of risk given by the inverse of $\mathbb{E}(T_i|w_i, v_i)$. We therefore replace $Risk = \Phi(w_i'\beta_2 + v_i)$ in Models I and II by $Risk = [\mathbb{E}(T_i|w_i, v_i)]^{-1}$ in the business training decision process. We present the results of the estimation for the bivariate mixed model in Table 4 in the next section.

5 Econometric results

5.1 Bivariate probit model

The estimations of the bivariate probit models are presented in Table 3.¹⁸ Columns (1) and (3) contain the estimates for equations (1) (Model I) and (3) (Model II), where we test for a linear and a quadratic relationship between *Risk* and business training allocation respectively. Columns (2) and (4) contain the estimates for equation (2) using Model I and Model II respectively.

According to column (1), the linear relationship between *Risk* and business training is not significantly different from zero. Furthermore, according to column (2), business training does not significantly impact repayment, since $\hat{\alpha}_1$ is not significant either. Therefore neither H1 nor H2 is verified in Model I.

In contrast, the estimation of Model II, where we account for a non-linear relationship between *Risk* and business training, yields considerably different results. Both $\hat{\lambda}_1$ and $\hat{\lambda}_2$ are significant at 1% level with opposite signs in column (3). Therefore H1 is verified in Model II: the intrinsic risk of a borrower non-linearly impacts his/her likelihood of receiving business training. More specifically, the probability of receiving business training first increases with borrowers' risk and then, beyond a certain threshold decreases. We can compute, using the estimates in column (3), the threshold beyond which the probability of receiving business training begins to decrease with risk. To do so we use the derivative:

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

¹⁸In 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 0.36 and negative otherwise. We estimated the $Risk = \Phi(w_i'\hat{\beta}_2 + v_i)$ for each borrower in our dataset. 81% of borrowers have an estimated risk lower than 0.36 and 19% have an estimated risk higher than this threshold.

Similar to Model I, business training does not significantly impact loan repayment in Model II, since $\hat{\alpha}_1$ is non-significantly different from zero in column (4). Therefore, H2 is not verified in Model II either. We conclude that business training does not impact the likelihood of defaulting.

Table 3: Determinants of Business Training and Default Processes

Model	Bivariate probit (Model I)		Bivariate probit (Model II)					
	(1)	(2)	(3)	(4)				
Dependent variable:	Business training	Defaulting	Business training	Defaulting				
Explanatory variables:								
Risk ($\hat{\lambda}_1$)	0.36	(0.51)	5.97***	(2.28)				
Risk ² ($\hat{\lambda}_2$)			-8.21***	(3.03)				
Other applications	1.07***	(0.19)	1.29***	(0.26)				
Honor loan	0.5***	(0.16)	0.64***	(0.20)				
Sent by a mainstream bank	-0.55***	(0.19)	-0.65***	(0.22)				
$\hat{\rho}_1$	0.03	(0.45)	0.24	(0.27)				
Business training (direct effect) ($\hat{\alpha}_1$)		-0.11	(0.43)	0.15	(0.31)			
Male		0.7***	(0.26)	0.81***	(0.26)			
Education (direct effect)		-0.25**	(0.11)	-0.28***	(0.09)			
Single		0.1	(0.25)	0.31	(0.24)			
Unemployed at least 12 months		0.36	(0.24)	0.16	(0.21)			
Household income (kEUR)		-0.41**	(0.16)	-0.52***	(0.18)			
Household expenses (kEUR)		0.92***	(0.3)	1.20***	(0.36)			
Low personal investment		0.5**	(0.23)	0.47**	(0.23)			
Assets (kEUR)		-0.02**	(0.01)	-0.02***	(0.01)			
Food and accommodation sector		0.06	(0.42)	0.32	(0.41)			
Gross margin(EUR)/Sales(EUR)		-1.21**	(0.56)	-0.93*	(0.51)			
Business training (indirect effect)		-12.25	(892.58)	-2.20	(1.80)			
Education (indirect effect)		0.07	(0.15)	0.28***	(0.02)			
Intercept	-0.71***	(0.22)	0.09	(0.69)	-1.09***	(0.32)	-0.41	(0.57)
Business cycles		Yes		Yes				
-2 Log Likelihood		644		639				
Observations		340		340				

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

The effects of other control variables in Model II are similar to those in Model I. 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 probably the riskiest) or have been granted a co-financing credit by the mainstream bank (and are probably the least risky). In both these situations, we expect that such individuals will be the least likely to be assigned to a training program, due to a potential behavioral effect on their self-confidence

(for the riskiest individuals) or due to their expected good performance ruling out any need for business training (for the least risky individuals). $\hat{\rho}_1$ is not significant, suggesting that adding borrower's risk to the business training equation is sufficient to control for the interdependence of the two processes and potential endogeneity.

Turning to the default equation, male clients are significantly more likely to default than female clients. A similar result is reported by [D'Espallier et al. \(2011\)](#) for MFIs in developing countries. Higher education (measured by number of diplomas) significantly decreases a client's riskiness. Household income and expenses are respectively strong negative and positive determinants of the likelihood of defaulting. Borrowers with low personal investment and low assets are significantly riskier. Finally, the gross margin-to-sales ratio is associated with lower credit risk.

Concerning heteroscedasticity, the indirect effect of business training is not significant in either model. In contrast, the indirect effect of education is significant at 1% in Model II, suggesting that a higher level of education significantly increases the variance of the unobserved individual heterogeneity term, v_i . In other words, there is more uncertainty about risk of default with more educated borrowers.

5.2 Bivariate mixed model

The estimations of the bivariate mixed models are presented in Table 4. The equivalent specifications for Models I and II are given in columns (1)-(2) and columns (3)-(4) respectively. According to column (1), the linear relationship between *Risk* (now measured by the inverse of expected survival time of the loan)¹⁹ and business training is significant, but only at 10% level. Furthermore, according to column (2), business training does not significantly impact loan survival time, since $\hat{\alpha}_1$ is not significant. Therefore H1 is verified in Model I: the intrinsic risk of a borrower increases his/her likelihood of receiving business training, although this relationship is only significant at 10% level. Akin to the bivariate probit model, H2 is not verified in Model I.

Importantly, Model II, where we account for a non-linear relationship between *Risk* and business training, yields considerably different results. Both $\hat{\lambda}_1$ and $\hat{\lambda}_2$ are significant at 1% and 5% levels respectively with

¹⁹We multiply the *Risk* variable by 100 to scale down the estimated coefficients and render them comparable to other loadings.

Table 4: Determinants of Business Training and Inverse of Survival Time

Model	Bivariate mixed (Model I)		Bivariate mixed (Model II)					
	(1)	(2)	(3)	(4)				
Dependent variable:	Business training	Inverse of Survival Time	Business training	Inverse of Survival Time				
Explanatory variables:								
Risk ($\hat{\lambda}_1$)	1.61*	(0.97)	1.22***	(0.43)				
Risk ² ($\hat{\lambda}_2$)			-0.22**	(0.10)				
Other applications	1.13***	(0.18)	1.18***	(0.19)				
Honor loan	0.52***	(0.17)	0.56***	(0.18)				
Sent by a mainstream bank	-0.57***	(0.2)	-0.56***	(0.21)				
$\hat{\rho}_1$	-0.22	(0.32)	0.29*	(0.16)				
Business training (direct effect) ($\hat{\alpha}_1$)		-0.19	(0.4)	-1.29***	(0.14)			
Male		0.64**	(0.25)	0.63***	(0.11)			
Education (direct effect)		-0.25**	(0.11)	-0.52***	(0.06)			
Single		-0.07	(0.23)	-0.39***	(0.08)			
Unemployed at least 12 months		0.73***	(0.23)	0.74***	(0.09)			
Household income (kEUR)		-0.16	(0.13)	-0.6***	(0.06)			
Household expenses (kEUR)		0.62**	(0.26)	0.99***	(0.1)			
Low personal investment		0.64***	(0.21)	0.71***	(0.09)			
Assets (kEUR)		-0.02**	(0.01)	-0.01**	(0.004)			
Food and accommodation sector		-0.03	(0.38)	0.27*	(0.15)			
Gross margin(EUR)/Sales(EUR)		-1.22**	(0.51)	-1.43***	(0.19)			
Business training (indirect effect)		-0.38	(0.37)	-0.08	(0.07)			
Education (indirect effect)		0.01	(0.09)	0.15***	(0.03)			
Weibull parameter (σ)		1.63***	(0.33)	3.91***	(0.47)			
Intercept	-0.87***	(0.2)	-6.53***	(0.54)	-0.94***	(0.18)	-5.13***	(0.24)
Business cycles			Yes			Yes		
-2 Log Likelihood		1616		1603				
Observations		340		340				

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

opposite signs in column (3). Therefore, H1 is again verified in Model II: the intrinsic risk of a borrower non-linearly impacts his/her likelihood of receiving business training. Similar to the bivariate probit model, the probability of receiving business training first increases with borrower's risk and then, beyond a certain threshold, decreases.

Crucially, the coefficient of business training ($\hat{\alpha}_1$) becomes significant in column (4), meaning that business training increases loan survival time (i.e. reduces borrower's risk), thereby increasing the expected return on the loan for the MFI. This result suggests that business training actually does increase a business's chances of success. H2 is thus verified in the bivariate mixed Model II: business training positively impacts loan repayment when we control for the process of assignment to business training and its possible behavioral effects.

The results of Model I and Model II highlight the need to control for the non-linear relationship between borrowers' risk and business training in order to capture the effect of business training. Our findings show that this relationship is complex, potentially due to behavioral reactions generated by it among training

beneficiaries. We further analyze this possibility in our theoretical model (see Section 7). Our results also confirm the importance of the informational content of longitudinal data in the evaluation of business training impact.²⁰ Ignoring behavioral effects and the longitudinal aspect of defaulting loans appears to bias results on training efficiency, which may at least partly explain the mixed results in terms of business training efficiency reported in the existing literature.

The coefficients of other controls are in line with the bivariate probit model, although a few differences are worth mentioning. According to column (4), being single increases the survival time of the loan. In contrast, businesses run by clients who are long-term unemployed or in the food and accommodation sector are significantly riskier. The Weibull parameter is significant and positive, suggesting that risk is increasing with time.

To check the robustness of our results, we propose two alternative models accounting for the MFI's selection process during the loan approval stage, using the information on rejected applicants available in our dataset. First, in the next section we correct for selection bias (Heckman, 1979) through trivariate models where we add to our baseline models an equation accounting for the MFI's binary decision to grant or reject a loan. Second, Appendix 9.3 contains the results of a nested logit model where we allow loan approval and training allocation decisions to take place concomitantly.²¹

6 Robustness checks: Correcting for selection bias

Bivariate models are estimated only for granted loans, as an individual can only be assigned to a training program if he/she has actually been granted a microcredit. In this section we add to the previous bivariate models a third process, namely the loan approval decision, which allows us to correct for selection bias. Adding the approval process will also reveal whether the MFI is choosing its clients optimally in terms of their expected performance. This additional equation for the binary decision loan approval or not, y_{0i} , writes

²⁰The non-significance of business training in the bivariate probit model might be due to reduced variability in the risk variable, which is a dummy.

²¹We thank an anonymous referee for pointing out a possible scenario where loan approval and training allocation decisions are not strictly sequential.

as follows:

$$y_{0i}^* = \beta_0 w_i' + \eta_0 \mathbf{B}_{0i} + \epsilon_{0i} \quad y_{0i} = \begin{cases} 1 & \text{if } y_{0i}^* > 0 \text{ Approval} \\ 0 & \text{if } y_{0i}^* \leq 0 \text{ Otherwise} \end{cases} \quad (6)$$

We use the same explanatory variables w_i as in risk equation, as suggested by Roszbach (2004). We moreover introduce into the approval equation business cycle variables (\mathbf{B}_{0i}) that may impact the MFI's decision to grant the loan or not. \mathbf{B}_{0i} corresponds to the rate of increase in business failures and new business start-ups in the sector of enterprise i at the time of loan approval, and one quarter and two quarters before loan approval. The business cycles operating before loan approval will enable the identification of the trivariate model.²² In this model, we allow for correlation between the two decisions (approval and business training) and the risk equation by imposing a similar structure on error terms having an equivalent error composition and the same distributional assumptions:

$$\epsilon_{0i} = \rho_0 v_i + \epsilon_{0i}^0$$

The results for the trivariate probit and mixed models are presented in Tables 5 and 6 respectively. In column (1) we report the results for the selection equation, in column (2) we show the results for the business training allocation equation and in column (3) we present the results for the risk equation. We only present the specifications accounting for the non-linear relationship between business training and borrowers' risk (i.e. Model II).

Controlling for selection bias does not alter our main results. According to column (2) (Tables 5 and 6), $\hat{\lambda}_1$ and $\hat{\lambda}_2$ are both significant with opposite signs, suggesting that the probability of business training assignment first increases with risk and then, beyond a certain threshold, decreases. Therefore, H1 is supported by the trivariate probit and mixed models, suggesting a robust non-linear relationship between business training allocation and borrowers' risk.

Additionally, according to column (3) (Tables 5 and 6), $\hat{\alpha}_1$ is only significant in Table 6, suggesting that business training decreases borrowers' risk only in the trivariate mixed model. Therefore, similar to our

²²In the risk equation, business cycles are introduced at the beginning of the loan (and one and two quarters later), whereas in the approval equation, business cycles are introduced at approval, which does not necessarily coincide with the beginning of the loan. There is generally no overlap between the business cycle variables in the approval and risk equations.

Table 5: Determinants of Approval, Business Training and Default Processes

Model	Trivariate probit		
Dependent variable:	(1)	(2)	(3)
	Approval	Business training	Defaulting
Explanatory variables:			
Risk ($\hat{\lambda}_1$)		2.15* (1.13)	
Risk ² ($\hat{\lambda}_2$)		-2.83*** (1.03)	
Other applications		1.09*** (0.17)	
Honor loan		0.53*** (0.17)	
Sent by a mainstream bank		-0.57*** (0.19)	
$\hat{\rho}_1$		-0.13 (0.31)	
Business training (direct effect) ($\hat{\alpha}_1$)			0.09 (0.49)
Male	-0.29 (0.28)		1.03*** (0.39)
Education (direct effect)	-0.03 (0.09)		-0.19 (0.14)
Single	0.02 (0.26)		0.18 (0.28)
Unemployed at least 12 months	-0.72** (0.35)		0.59** (0.26)
Household income (kEUR)	0.22 (0.14)		-0.51** (0.2)
Household expenses (kEUR)	-0.43 (0.29)		1.16** (0.45)
Low personal investment	-0.46 (0.3)		0.65** (0.31)
Assets (kEUR)	0.01 (0.01)		-0.03*** (0.01)
Food and accommodation sector	-0.96** (0.4)		0.78 (0.67)
Gross margin(EUR)/Sales(EUR)	-0.78 (0.59)		-0.99 (0.63)
$\hat{\rho}_0$	-2.14** (1.03)		
Business training (indirect effect)			0.35 (0.33)
Education (indirect effect)			0.08 (0.27)
Intercept	1.26** (0.64)	-0.89*** (0.28)	-0.89*** (0.28)
Business cycles	Yes		Yes
-2 Log Likelihood		1537	
Observations		662	

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

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

Model	Trivariate mixed		
Dependent variable:	(1)	(2)	(3)
	Approval	Business training	Inverse of Survival Time
Explanatory variables:			
Risk ($\hat{\lambda}_1$)		2.59*** (0.86)	
Risk ² ($\hat{\lambda}_2$)		-0.88** (0.38)	
Other applications		1.11*** (0.18)	
Honor loan		0.53*** (0.17)	
Sent by a mainstream bank		-0.57*** (0.19)	
$\hat{\rho}_1$		-0.20 (0.17)	
Business training (direct effect) ($\hat{\alpha}_1$)			-0.41** (0.16)
Male	-0.12 (0.11)		0.59*** (0.14)
Education (direct effect)	-0.01 (0.04)		-0.31*** (0.09)
Single	-0.001 (0.12)		-0.18* (0.11)
Unemployed at least 12 months	-0.31*** (0.11)		0.84*** (0.11)
Household income (kEUR)	0.11* (0.06)		-0.22*** (0.07)
Household expenses (kEUR)	-0.22* (0.12)		0.41*** (0.14)
Low personal investment	-0.19* (0.12)		0.83*** (0.10)
Assets (kEUR)	0.003 (0.002)		-0.01 (0.005)
Food and accommodation sector	-0.46*** (0.17)		-0.63*** (0.18)
Gross margin(EUR)/Sales(EUR)	-0.45 (0.27)		-1.39*** (0.23)
$\hat{\rho}_0$	0.24* (0.14)		
Business training (indirect effect)			-0.09 (0.08)
Education (indirect effect)			0.13*** (0.04)
Weibull parameter (σ)			3.40*** (0.54)
Intercept	0.60** (0.28)	-0.92*** (0.18)	-6.38*** (0.29)
Business cycles	Yes		Yes
-2 Log Likelihood	2485		
Observations	662		

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

baseline results, H2 is only supported by the trivariate mixed model. We conclude that business training is indeed efficient in increasing loan survival time, when the non-linear relationship between business training allocation and borrowers' risk is accounted for.

As expected, the coefficients in the approval equation are generally of the opposite sign to those in the risk equation. However, only two variables significantly impact approval according to column (1) in Table 5. Long-term unemployed applicants and businesses in the food and accommodation sector are less likely to be accepted by the MFI. Three more variables are significant in column (1), Table 6. Larger household income increases the probability of loan approval, whereas higher household expenses and low personal investment decrease it. However, other variables which significantly impact borrowers' risk are not significant in the approval equation, suggesting that the MFI is not perfectly optimizing its approval process with respect to clients' creditworthiness (Roszbach, 2004, reaches similar conclusions using data on consumer loans from a Swedish bank).

Similar to our baseline models, in the trivariate mixed model the indirect effect of business training is not significant and the indirect effect of education is significantly positive, suggesting that default risk uncertainty increases for better educated individuals. Finally, $\hat{\rho}_0$ is significant in the trivariate models, suggesting that the selection bias is indeed present and has to be taken into account.

In this section, loan approval was treated as strictly sequential (and anterior) to business training allocation. In the Appendix, 9.3, we allow these two processes to be concomitant (the MFI chooses from rejecting a loan, accepting it without training and accepting it with training) through a nested logit model. The results, presented in Table 7, are similar to those reported for the trivariate probit model. We find the same non-linear relationship between intrinsic risk and likelihood of being assigned to business training; and a non-significant (but this time negative) relationship between business training and default. The non-significance of this last relationship may again be due to the low variability of our default variable (which is a dummy).

7 Business training allocation and reverse asymmetric information

In this section, we present a theoretical model aimed at rationalizing the non-linear effect of the borrower's intrinsic risk on his/her probability of being assigned to business training, highlighted in our empirical work.

This model is based on the psychological or behavioral effect that business training can have on borrowers unaware of their own risk (or type). This mechanism, termed the “looking-glass self” effect by [Cooley \(1902\)](#), is likely to occur when the principal (here the MFI) has better information than the agent (here the borrower) (see for example [Benabou and Tirole, 2003b](#)) on the agent’s characteristics (the quality of his/her project). The terms “reverse asymmetric information” or “informed principal models” then apply.

This situation can be expected in the microcredit market, where MFIs generally finance first-time micro-entrepreneurs who need financial backing to start a business, and who usually lack the necessary experience. Thus, microfinance institutions (for example through scoring models and/or their past experience) may well be better informed than micro-entrepreneurs about the potential of the project. In this case, the contract offered by the MFI can provide borrowers with information about themselves, thereby impacting their beliefs and shaping their behavior. We model an MFI operating like most of the microcredit market, including our data-source MFI: no collateral is required and the same interest rate is applied to all borrowers. Assignment to business training is thus the only source of heterogeneity in the contracts. We show in this section that reverse asymmetric information can generate a non-linear relationship between borrowers’ risk and assignment to business training, consistent with our empirical analysis.

Consider an agent, a borrower, who has a project for which he/she needs financing. We assume that borrowers have no collateral and no personal investment. They need to borrow from the bank the total funds for the project, which we normalize to 1. We consider, as in the empirical analysis, that the funding process is in two steps: (i) first, the MFI chooses to reject or approve a loan, and (ii) second, it makes the training allocation decision for approved projects.

If undertaken, the project generates a return, ρ , in the case of success and 0 in the case of failure. The principal, the MFI, demands a return of $R = 1 + r$ in the case of success with $R < \rho$, where r is the fixed interest rate. The MFI receives 0 in the case of failure. The probability of success (denoted $p(\theta, h, e)$) depends on borrower type θ , borrower effort e and level of business training from the MFI h . We assume the probability of success to be increasing in these three terms. The parameter θ represents the intrinsic probability of success (or type) of the borrower, (i.e. $p(\theta; 0; 0) = \theta$), depending on borrower’s and project’s characteristics and excluding the effects of business training and effort (it therefore echoes the variable *Risk*

in our empirical work). We assume that the efficiency of effort and business training are both decreasing with type.

Assumption 1. *The probability of success $p(\theta, h, e)$ is such that $\frac{\partial^2 p}{\partial \theta \partial e} \leq \frac{\partial^2 p}{\partial \theta \partial h} \leq 0$*

This assumption is pretty standard and the second inequality corresponds to Assumption 3 in [Benabou and Tirole \(2003a\)](#). It moreover means that borrower's type has a stronger impact on the efficiency of effort than on the efficiency of training.

Furthermore, effort is costly for the borrower and business training is costly for the MFI. The respective costs are denoted by $\psi(\theta, e)$ and $\varphi(h)$. We hence assume that the (psychological) cost of effort is type-dependent and that it is decreasing with type.

Assumption 2. *The cost of effort is such that $\psi(\theta, 0) = 0$ and is decreasing with type : $\frac{\partial \psi}{\partial \theta} \leq 0$*

Regarding the MFI objective, we assume that once a borrower is accepted, the MFI either maximizes profit or minimizes loss on this borrower. The end of the section discusses the overall objective of the MFI. We follow the standard approach in banking modeling by assuming that the MFI is risk neutral so that, once the project is accepted, the objective function of the MFI is given by :

$$p(\theta; h; e)R - \varphi(h)$$

To simplify the model, we additionally assume that the borrower is risk neutral, so that the utility of the borrower is given by:

$$p(\theta; h; e)(\rho - R) - \psi(\theta; e)$$

We analyze two information structures. In the first, the information is perfect and symmetric: both the borrower and the MFI observe borrower's type. The MFI chooses h and the borrower chooses e simultaneously. We focus on cases where, under perfect information, the MFI provides a level of business training decreasing with type.²³ This means that, in the absence of an asymmetric information effect, the allocation of business training is like bad news for borrowers (since it reflects a low probability of success). In the

²³Our aim is here to show that under plausible assumptions, reverse asymmetric information can create a non-linear relationship between business training allocation and borrowers' type.

second configuration, we assume reverse asymmetric information, that is, a situation where borrowers do not know their type, while the MFI does. As mentioned above, this informational setting is particularly relevant for the microcredit market, where inexperienced borrowers meet experienced MFIs. In this case, the level of business training chosen by the MFI (h) also conveys information about the borrowers' type and might influence their behavior. In other words, by observing h , borrowers form a belief about their type that leads them to some level of effort. When choosing h , the MFI internalizes this mechanism, which shapes its profit through borrowers' effort. We show that, unlike under symmetric information, there can be a non-monotonic relationship between business training and borrower type in some Perfect Bayesian Equilibria. In other words, reverse asymmetric information could explain the pattern of business training allocation found in the empirical analysis.

To build our theoretical argument, we present a simple discrete version of the model, with two levels of effort and business training ($e \in \{0, 1\}$, $h \in \{0, 1\}$) and three types of borrowers, namely weak-, medium- and strong-type borrowers: $\theta \in \{W, M, S\}$.²⁴ We assume $\varphi(0) = 0$, $\varphi(1) = \phi$ and denote the efficiencies of training and effort $\Delta_h p(\theta, e) \equiv p(\theta, 1, e) - p(\theta, 0, e)$ and $\Delta_e p(\theta, h) = p(\theta, h, 1) - p(\theta, h, 0)$.

From assumption 1, $\Delta_e p(\theta, h)$ and $\Delta_h p(\theta, e)$ are decreasing with θ .

As explained above, our aim is to show that reverse asymmetric information can lead to the non-monotonic relationship found in our empirical analysis. We therefore focus on simple situations in which the relationship between training and type is monotonic under symmetric information. This would be the case in our simple discrete model under the following plausible assumptions regarding the MFI and borrowers' behavior when information is perfect.

Assumption 3. • *The MFI is not interested in training the strong-type borrowers:*

$$\forall e, \Delta_h p(W, e) \geq \Delta_h p(M, e) \geq \frac{\phi}{R} \geq \Delta_h p(S, e)$$

- *The cost of effort is such that, when informed about their type, only strong-type agents optimally exert effort:*

$$\forall h, \frac{\psi(M, 1)}{\rho - R} \geq \Delta_e p(M, h) \geq \Delta_e p(S, h) \geq \frac{\psi(S, 1)}{\rho - R} \text{ and } \frac{\psi(W, 1)}{\rho - R} \geq \Delta_e p(W, h)$$

²⁴A more general continuous model can be found in the working paper version of the paper (Bourlès et al., 2015)

As mentioned previously, the funding process takes place in two stages: a selection stage where the MFI rejects or approves a project, followed by a business training allocation stage where the MFI decides whether of not to train approved borrowers. Backward induction leads us to first focus the second stage (i.e. training allocation).

7.1 Business training allocation

First, given the above assumptions, the following remark holds:

Remark 1. *Under perfect symmetric information, Assumption 3 leads to a situation where the MFI provides business training to the two weakest types, W and M (if approved), and does not provide business training to the strongest type, S . Borrowers of type S provide effort but the weakest types M and W do not.*

Thus, under perfect information, weak-type borrowers are pooled with medium-type borrowers.

We now assume reverse asymmetric information. In this case, the appropriate equilibrium concept is “Perfect Bayesian Equilibrium” (PBE). We need to consider several cases where projects were approved during the selection stage.

First, let us consider first that projects of all three types are approved. Under reverse asymmetric information, borrowers are not aware of their 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/her type from observing the MFI’s decision on business training. We 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 M-type borrowers. In this case, borrowers observing that they are not assigned to training infer that they are either weak (W) or strong (S) type. Let us denote by α the probability that a borrower aware of being S- or W-type is actually S-type ($(1 - \alpha)$ is then the probability that he/she is actually W-type). In other words, α represents the borrower’s belief that he/she is strong-type when he/she observes that the MFI chooses not to train him/her. Correlatively, in the considered equilibrium, a borrower observing that the MFI has decided to train him/her is convinced that his/her type is M. This leads to the following proposition:

Proposition 1. *Under reverse asymmetric information, if all projects are approved, there exists a PBE*

(denoted by E^*) where the MFI provides business training only to M-type borrowers, S- and W-type borrowers exert effort and M-type do not, if:

$$\alpha \Delta_{ep}(S, 0) + (1 - \alpha) \Delta_{ep}(W, 0) \geq \alpha \frac{\psi(S, 1)}{(\rho - R)} + (1 - \alpha) \frac{\psi(W, 1)}{(\rho - R)} \quad (7)$$

and

$$\Delta_{hp}(W, 0) - \Delta_{ep}(W, 0) \leq \frac{\phi}{R} \leq \Delta_{hp}(M, 0) - \Delta_{ep}(M, 0) \quad (8)$$

As $\Delta_{hp}(\theta, 0)$ and $\Delta_{ep}(\theta, 0)$ are decreasing with θ , condition (8) implies that $\Delta_{ep}(W, 0) - \Delta_{ep}(M, 0)$ has to be large; that is, that effort has to be more efficient for W-type borrowers than for M-type ones.

Under condition (8) the perfect information outcome is not a PBE. Indeed, such an equilibrium would imply that absence of training convinces the borrower that he/she is an S-type, and therefore leads him/her to exert effort. But as $\Delta_{hp}(W, 0) - \Delta_{ep}(W, 0) \leq \frac{\phi}{R}$, that would induce the principal not to train W-type borrowers.

It can even be shown that under conditions (7) and (8), E^* is the only semi-separating PBE (in pure strategies) when projects of all types are approved.²⁵ Indeed, under (8) we have $p(M, 1, 1)R - \phi \geq p(M, 1, 0)R - \phi \geq p(M, 0, 1)R \geq p(M, 0, 0)R$, so that the MFI always trains M-type borrowers in any PBE. In a semi-separating equilibrium, M-types can hence be pooled either with W-types or with S-types. Pooling them with W-types corresponds to the perfect information outcome, which is not a PBE. Pooling M-types with S-types (and hence training both) induces W-types (not trained and aware of their type) to exert no effort. This is not a PBE, since the MFI obtains a higher return by training them (since $p(W, 1, e)R - \phi \geq p(W, 0, 0)R$). We thus assume in the following that when all the projects are approved, the MFI chooses E^* , where W-types are pooled with S-types.

We now assume that W-type projects are rejected. Under condition (8), when only M and S-types are approved, the only equilibrium is the perfect information one (since $\frac{\phi}{R} \leq \Delta_{hp}(M, 0) - \Delta_{ep}(M, 0)$ no pooling equilibrium can exist).

²⁵A pooling equilibrium in which all borrowers are assigned to business training and all provide effort can also exist. As is always the case with pooling PBE, it however requires stringent conditions on beliefs outside the equilibrium (that is, when borrowers are not trained). We therefore rule out this equilibrium and focus in the following on E^* .

Proposition 2. *If only M and S-type projects are approved, then in the second stage the MFI provides training only to M-type borrowers, S-types exert effort and M-types do not.*

Finally, by assumption 3, if only S-type projects are approved, then the MFI does not provide training and all agents exert effort.

7.2 Selection stage

In the selection stage, the MFI bases its decision on whether or not to approve a project on anticipated business training allocation. Thus, reverse asymmetric information can lead to an increase in approvals of W-type borrowers. As stated in the following proposition, this holds both for MFIs seeking to maximize their profits during the selection stage (we term these MFIs “for-profit”), and for MFIs whose objective is to increase their outreach while remaining sustainable (we term these MFIs “non-profit”).

Proposition 3. *Under conditions (7) and (8), the MFI earns a greater expected profit under reverse asymmetric information. Reverse asymmetric information then increases the outreach for a non-profit MFI if*

$$p(W, 0, 1)R < 1 + \phi \tag{9}$$

and for a for-profit MFI if

$$p(W, 0, 1)R \geq 1 \tag{10}$$

on top of (9).

As shown above, the only difference between symmetric and reverse asymmetric information concerns W-type borrowers, if approved. Under symmetric information they do not exert effort and receive business training; whereas, in E^* they do not receive business training but exert effort. Thus, under condition (8), the MFI makes greater profit on W-type projects (and thus greater total profit) under reverse asymmetric information. MFIs using cross-subsidization (i.e. non-profit MFIs)²⁶ can then finance more W-type projects under reverse asymmetric information, in cases where they have negative expected profit for W-type projects

²⁶Cross-subsidization corresponds to situations where the MFI uses the profits it makes on some borrowers to sustain lending to other borrowers on which it earns negative (expected) profits (Armendariz and Szafarz, 2011).

under symmetric information (i.e. under equation (9)). This also applies to for-profit MFIs, provided they also make positive expected profits for W-type borrowers under reverse asymmetric information (condition (10)).

8 Conclusion

This paper analyzes the effect of business training on microcredit repayment. The originality of our approach with respect to the existing literature is that we take into account the process of allocation to business training and its possible behavioral consequences for microborrowers.

We first reveal empirically, using bivariate probit and mixed models, that the business training allocation process is complex and non-linear in its relationship to borrowers' risk. More particularly, we show that the probability of being assigned to business training first increases with borrowers' intrinsic risk and then, beyond a certain threshold, decreases. This relationship is found to be robust to different measures of risk (probability of defaulting or the inverse of loan survival time).

Controlling for the business training allocation process and this non-linear relationship, we show that business training is efficient since it increases the survival time of loans (although direct effect on probability of default is not significant).

We moreover show that these two results (the non-linearity and the beneficial effect of training on loan survival time) are robust to correction for the MFI's selection bias, using data on rejected applicants.

Finally, we propose a novel theoretical explanation for the non-linear effect of intrinsic risk on business training allocation, through a reverse asymmetric information model. We show that an MFI can use its superior information on borrowers' risk to increase effort by microentrepreneurs. This enables them to extend their outreach to riskier borrowers, which is the main objective of MFIs striving to alleviate financial exclusion.

One of the weaknesses of our dataset consists in our lack of access to the ex-ante evaluation of borrowers' risk by the MFI. We therefore have to estimate it using a probit or a survival time model. Access to such information would ease the identification and the interpretation of our results.

In future work it would be worthwhile to testing our last theoretical result revealing a beneficial effect of

reverse asymmetric information on outreach to riskier borrowers. One way to test this effect would be to consider borrowers heterogeneous with respect to expertise in their project and their ability to succeed. Unfortunately, the current dataset does not contain enough observations of borrowers experienced in business creation and management.

More generally, our work opens the way to further exploring how reserve asymmetric information could shape microcredit markets. Beyond training allocation, one fruitful avenue for future research would consist in analyzing other ways that MFIs could use their superior information strategically to mitigate the moral hazard problems plaguing microcredit markets in the absence of collateral. It might, for example, be interesting to analyze how superior information can modify the dynamics of microcredit contracts in settings where borrowers can apply several times for a microcredit within the same MFI (progressive lending) or where borrowers can apply for a microcredit from several MFIs (competitive markets).

9 Appendix

9.1 Bivariate probit and bivariate mixed models: The likelihood functions

In the first model defined by the simultaneous probit equations (2) and (3), the individual contribution to the likelihood function given the common factor v_i can be written as follows:

$$\begin{aligned}
 Li(\theta|y_{1i}, y_{2i}, x_i, w_i, v_i) &= \underbrace{\Phi\left(x'_i\beta_1 + \lambda_1\Phi(w'_i\beta_2 + v_i) + \lambda_2\left[\Phi(w'_i\beta_2 + v_i)\right]^2 + \rho_1v_i\right)}_{P(y_{1i}=1|v_i, \dots)}^{y_{1i}} \cdot \\
 &\underbrace{\left[1 - \Phi\left(x'_i\beta_1 + \lambda_1\Phi(w'_i\beta_2 + v_i) + \lambda_2\left[\Phi(w'_i\beta_2 + v_i)\right]^2 + \rho_1v_i\right)\right]}_{P(y_{1i}=0|v_i, \dots)}^{(1-y_{1i})} \cdot \\
 &\underbrace{\Phi(w'_i\beta_2 + \eta\mathbf{B}_i + \alpha_1y_{1i} + v_i)}_{P(y_{2i}=1|v_i, y_{1i}, \dots)}^{y_{2i}} \cdot \underbrace{\left[1 - \Phi(w'_i\beta_2 + \eta\mathbf{B}_i + \alpha_1y_{1i} + v_i)\right]}_{P(y_{2i}=0|v_i, y_{1i}, \dots)}^{(1-y_{2i})}
 \end{aligned}$$

In the bivariate mixed model, the loan survival time is used and it follows the Weibull distribution given by (4). Hence, the individual contribution to the likelihood function conditional on v_i can be written as follows:

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

Hence, in the two models, we need 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, which is only defined for individuals with granted loans:

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

9.2 Trivariate probit and trivariate mixed models: The likelihood functions

We extend the previous models by adding a third process, the loan approval decision defined by the probit equation (6). For each model, the individual contribution to the likelihood function given the common factor

v_i can be written, respectively, as follows:

$$\begin{aligned}
L_i(\theta|y_{0i}, y_{1i}, y_{2i}, w_i, x_i, v_i) &= \underbrace{\Phi\left(w'_i\beta_0 + \eta_0\mathbf{B}_{0i} + \rho_0v_i\right)}_{P(y_{0i}=1|v_i, \dots)}^{y_{0i}} \cdot \underbrace{\left[1 - \Phi\left(w'_i\beta_0 + \eta_0\mathbf{B}_{0i} + \rho_0v_i\right)\right]}_{P(y_{0i}=0|v_i, \dots)}^{(1-y_{0i})} \cdot \\
&\underbrace{\Phi\left(x'_i\beta_1 + \lambda_1\Phi(w'_i\beta_2 + v_i) + \lambda_2\left[\Phi(w'_i\beta_2 + v_i)\right]^2 + \rho_1v_i\right)}_{P(y_{1i}=1|v_i, y_{0i}=1, \dots)}^{y_{0i}y_{1i}} \cdot \\
&\underbrace{\left[1 - \Phi\left(x'_i\beta_1 + \lambda_1\Phi(w'_i\beta_2 + v_i) + \lambda_2\left[\Phi(w'_i\beta_2 + v_i)\right]^2 + \rho_1v_i\right)\right]}_{P(y_{1i}=0|v_i, y_{0i}=1, \dots)}^{y_{0i}(1-y_{1i})} \cdot \\
&\underbrace{\left[\Phi(w'_i\beta_2 + \eta\mathbf{B}_i + \alpha_1y_{1i} + v_i)\right]}_{P(y_{2i}=1|v_i, y_{0i}=1, y_{1i}, \dots)}^{y_{0i}y_{2i}} \cdot \underbrace{\left[1 - \Phi(w'_i\beta_2 + \eta\mathbf{B}_i + \alpha_1y_{1i} + v_i)\right]}_{P(y_{2i}=0|v_i, y_{0i}=1, y_{1i}, \dots)}^{y_{0i}(1-y_{2i})}
\end{aligned}$$

and

$$\begin{aligned}
L_i(\theta|y_{0i}, y_{1i}, y_{2i}, w_i, x_i, v_i) &= \underbrace{\Phi\left(w'_i\beta_0 + \eta_0\mathbf{B}_{0i} + \rho_0v_i\right)}_{P(y_{0i}=1|v_i, \dots)}^{y_{0i}} \cdot \underbrace{\left[1 - \Phi\left(w'_i\beta_0 + \eta_0\mathbf{B}_{0i} + \rho_0v_i\right)\right]}_{P(y_{0i}=0|v_i, \dots)}^{(1-y_{0i})} \cdot \\
&\underbrace{\Phi\left(x'_i\beta_1 + \lambda_1E(T_i)^{-1} + \lambda_2E(T_i)^{-2} + \rho_1v_i\right)}_{P(y_{1i}=1|v_i, y_{0i}=1, \dots)}^{y_{0i}y_{1i}} \cdot \\
&\underbrace{\left[1 - \Phi\left(x'_i\beta_1 + \lambda_1E(T_i)^{-1} + \lambda_2E(T_i)^{-2} + \rho_1v_i\right)\right]}_{P(y_{1i}=0|v_i, y_{0i}=1, \dots)}^{y_{0i}(1-y_{1i})} \cdot \\
&\underbrace{\left[\sigma\mu_i^\sigma t_i^{\sigma-1} \exp\left\{-\left(\mu_i t_i\right)^\sigma\right\}\right]}_{f(t_i|v_i, y_{0i}=1, y_{1i}, \dots)}^{y_{0i}y_{2i}} \cdot \underbrace{\left[\exp\left\{-\left(\mu_i t_i\right)^\sigma\right\}\right]}_{P(T_i > t_i|v_i, y_{0i}=1, y_{1i}, \dots)}^{y_{0i}(1-y_{2i})}
\end{aligned}$$

Hence, in the two models, we need 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, which is now defined for the entire sample including the rejected applicants:

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

9.3 Nested logit

In this appendix we allow for the loan approval process and the business training allocation to occur concomitantly using a two-level nested logit model. In this setting, the MFI chooses for each applicant among three alternative decisions: rejecting the loan ($y = 0$), accepting it without business training ($y = 10$) or accepting it with business training ($y = 11$). This set of alternative decisions can then be partitioned into subsets (or nests), forming a hierarchical structure of decisions. The MFI's decision can be indeed modeled at two levels: first reject or accept the loan (first level), and, conditionally on approval, provide or not business training (second level). This nested structure allows accounting for the potential similarities between the last two alternatives.

The probability of each outcome can be written using standard logit models (for the details and the foundations of the nested logit models, see [Train, 2009](#)). The probability of these three choices can then be written as follows (we use the same set of covariates as in the previous models and denote by $\Lambda(\cdot)$ the logistic cumulative distribution function: $\Lambda(x) \equiv [1 + \exp(-x)]^{-1}$):

$$\begin{aligned}
\mathbb{P}(y_i = 0) &= \mathbb{P}(y_{0i} = 0) = 1 - \mathbb{P}(y_{0i} = 1) = \Lambda(-(w'_i\beta_0 + \eta_0\mathbf{B}_{0i} + \phi IV_i + \rho_0\nu_i)) \\
\mathbb{P}(y_i = 10) &= \mathbb{P}(y_{0i} = 1, y_{1i} = 0) = \mathbb{P}(y_{0i} = 1)\mathbb{P}(y_{1i} = 0|y_{0i} = 1) \\
&= \mathbb{P}(y_{0i} = 1) [1 - \Pr(y_{1i} = 1|y_{0i} = 1)] \\
&= \Lambda(w'_i\beta_0 + \eta_0\mathbf{B}_{0i} + \phi IV_i + \rho_0\nu_i) \Lambda\left(-\phi^{-1}(x'_i\beta_1 + \lambda_1 Risk + \lambda_2 Risk^2 + \rho_1\nu_i)\right) \\
\mathbb{P}(y_i = 11) &= \mathbb{P}(y_{0i} = 1, y_{1i} = 1) = \mathbb{P}(y_{0i} = 1)\mathbb{P}(y_{1i} = 1|y_{0i} = 1) \\
&= \Lambda(w'_i\beta_0 + \eta_0\mathbf{B}_{0i} + \phi IV_i + \rho_0\nu_i) \Lambda\left(\phi^{-1}(x'_i\beta_1 + \lambda_1 Risk + \lambda_2 Risk^2 + \rho_1\nu_i)\right)
\end{aligned}$$

where $IV_i \equiv \ln\left[1 + \exp\left(\Lambda\left(\phi^{-1}(x'_i\beta_1 + \lambda_1 Risk + \lambda_2 Risk^2 + \rho_1\nu_i)\right)\right)\right]$ is the inclusive value connecting the two decision levels.

The scale parameter ϕ can be interpreted as a measure of dissimilarity between the last two alternatives. Borrowers' intrinsic risk is proxied by $Risk = \Phi(w'_i\beta_2 + \nu_i)$. Hence, the individual contribution to the likelihood function conditional on ν_i can be written in the same manner as in appendix [9.2](#).

The results, presented in [Table 7](#), are similar to those reported for the trivariate probit model. We find

the same non-linear relationship between intrinsic risk and likelihood of being assigned to business training; and a non-significant (but this time negative) relationship between business training and default. The non-significance of this last relationship may again be due to the low variability of our default variable (which is a dummy).

The nested logit scale parameter is significant at 5% level. Overall, the coefficients of other controls in the approval and business training equations are in line with the trivariate probit model. Several control variables, such as Education, Single, Food and accommodation sector, and Gross margin/Sales become significant in the risk equation in the nested logit model whereas they were not significantly different from zero in the trivariate probit model.

Table 7: Nested Logit Model

Model	Nested logit			
	(1)	(2)		(3)
Dependent variable:	Approval	Business training		Defaulting
Explanatory variables:				
Risk ($\hat{\lambda}_1$)		8.14***	(1.13)	
Risk ² ($\hat{\lambda}_2$)		-20.67***	(2.28)	
Other applications		19.22***	(7.26)	
Honor loan		5.98**	(2.58)	
Sent by a mainstream bank		-7.62**	(3.26)	
$\hat{\rho}_1$		0.07	(0.04)	
Business training (direct effect) ($\hat{\alpha}_1$)				-0.08 (0.14)
Male	-0.24	(0.20)		0.41*** (0.03)
Education (direct effect)	-0.02	(0.07)		-0.07*** (0.01)
Single	-0.02	(0.22)		0.28*** (0.03)
Unemployed at least 12 months	-0.65***	(0.21)		0.10*** (0.03)
Household income (kEUR)	0.16	(0.11)		-0.27*** (0.02)
Household expenses (kEUR)	-0.37	(0.23)		0.88*** (0.04)
Low personal investment	-0.33	(0.22)		0.28*** (0.04)
Assets (kEUR)	0.004	(0.004)		-0.004*** (0.001)
Food and accommodation sector	-0.75**	(0.31)		-0.34*** (0.08)
Gross margin(EUR)/Sales(EUR)	-0.69	(0.51)		-0.56*** (0.09)
$\hat{\rho}_0$	-0.91***	(0.13)		
ϕ (nested logit parameter)	0.03**	(0.01)		
Business training (indirect effect)				-8.06 (48.58)
Education (indirect effect)				-4.43 (7.12)
Intercept	-0.87*	(0.52)	-0.57*** (0.13)	-0.80*** (0.13)
Business cycles	Yes			Yes
-2 Log Likelihood			1531.7	
Observations			662	

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

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