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BUSINESS TRAINING WITH A BETTER-INFORMED LENDER: THEORY AND
EVIDENCE FROM MICROCREDIT IN FRANCE

RENAUD BOURLÈS^a, ANASTASIA COZARENCO^b, DOMINIQUE HENRIET^c AND
XAVIER JOUTARD^d

In the microfinance sector, experienced lenders enjoy an information advantage over first-time entrepreneurs. Our study proposes an analysis of the business training provided on a par with microloans and its potential effect on borrowers' behavior. First, we present a simple theoretical mechanism showing that an information advantage concerning borrower risk can lead to a non-monotonic relationship between risk and business training provision. Second, using a hand-collected data set of loan applications to a French MFI, we empirically examine the relationship between business training provision and borrower risk, controlling for selection bias and endogeneity. The collected evidence supports the existence of a non-monotonic relationship and shows that business training significantly increases the survival time of loans. Our results are robust to alternative econometric models.

JEL Codes: C41, D82, G21.

Keywords: Business Training, Microcredit, Informed Lender.

1. INTRODUCTION

Should nascent entrepreneurs be offered business training on a par with financial services? What impact has business training on the behavior of borrowers and, as a result, on loan repayment? These questions are key to understanding the role of business training combined with financial services for both financial institutions and their clients. If business training indeed does play a role in the behavior and motivation of borrowers, for example by conveying information on project riskiness, its effects should be taken into account by lenders offering both financial and non-financial services. Assessing the workings of business training provision is key for policymakers, investors, donors, and other stakeholders.

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Behavioral responses of borrowers to business training provision are likely if the lender is in a better position than the borrower to estimate project risk. This framework is particularly suitable for situations where an experienced lender, having statistically accurate information, finances several first-time entrepreneurs facing similar economic conditions (Inderst, 2008; Inderst and Mueller, 2006). The information advantage of lenders has significant effects in credit markets. On the one hand, lending decisions (approving or rejecting a loan, loan size, interest rate, business training, and other contract terms) are informative for borrowers. As discussed in the sociological literature and, more recently, in economic studies (Benabou and Tirole, 2003a,b) lending decisions can either boost or undermine borrower motivation and self-perception. On the other hand, lenders should take behavioral responses into account when they decide on the type of loan agreement to be offered. This paper examines how behavioral effects affect lending decisions, in particular regarding business training provision.

We address this question in the context of microfinance for three main reasons. First, many Microfinance Institutions (MFIs) offer both financial and non-financial services to their clients,¹ for financial and human capital are major prerequisites for entrepreneurial success (Schreiner and Woller, 2003). This is especially true in developed countries where administrative constraints and barriers to entry can be discouraging (Schreiner and Morduch, 2002).

Second, MFIs provide banking services to financially underserved and inexperienced micro-entrepreneurs. Microfinance clients are often unemployed, have a lower education level, and start a business for the first time. In this market, the lender, thanks to its experience, geographical proximity, and statistical models (see Paravisini, Rappoport, and Schnabl, 2015; Treacy and Carey, 2000, for evidence of specialization in the banking industry and the role of rating models), is likely to be better informed than borrowers on project riskiness. Therefore, adopting the notion of “informed lending” by Inderst (2008) and Inderst and Mueller (2006), we consider that MFIs are better informed than borrowers regarding project risk. Admittedly, this assumption contrasts with the classical setting of asymmetric information, where the lender has to infer private information about borrower characteristics. While we do not neglect the importance of borrower-related private information, the assumption that specialized and experienced lenders can estimate project risk better than individual borrowers is particularly relevant if borrowers are first-time entrepreneurs creating businesses as a way out of unemployment (Bourlès and Cozarenco, 2018).

Third, in the microfinance context—where loans are not collateralized and interest rates are fixed—MFIs generally tailor the loan’s size to the applicant’s expected creditworthiness (Agier and Szafarz, 2013). However, regulation often imposes loan ceilings on MFIs

¹European microfinance institutions have been involved in business training since their emergence (Lammermann, Zamorano, and Guichandut, 2007). Over 57% of MFIs in Europe provide business development services in addition to microloans (Diriker, Landoni, and Benaglio, 2018) against about 25% of MFIs in developing countries (Garcia and Lensink, 2019). Non-financial services provision plays an important role in the microfinance sector (Schreiner and Morduch, 2002), a practice termed microfinance-plus (Biosca, Lenton, and Mosley, 2014a). Non-financial services take various forms, such as social services, business development services, and technical assistance (Garcia and Lensink, 2019). 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, Mosquera-Yon, and Masson, 2011).

(Cozarenco and Szafarz, 2018), limiting the freedom to adjust loan size. Therefore, assignment to training courses is the main source of heterogeneity that might trigger behavioral responses in borrowers. To the best of our knowledge, our study is the first to take into account behavioral responses to business training provision on the credit market.

The aim of this study is to analyze to what extent the information advantage held by lenders on project riskiness may trigger behavioral responses by borrowers, and how it affects lenders' decisions regarding their business training provision. First, we provide a simple theoretical reasoning that emphasizes the mechanisms through which this informational advantage (i.e., a situation where the MFI possesses better information on project risk than borrowers themselves) can crucially affect the training provision pattern. In particular, we point out that through the behavioral response of the borrower, informed lending can lead to a non-monotonic relationship between training provision and project (or borrower) risk.²

Second, using a unique data set on applicants to a French MFI, we conduct an empirical assessment of the relationship between training provision and borrower risk. Our main challenges are (i) to infer borrower risk, (ii) to deal with endogeneity arising from non-random assignment to a business training course, and (iii) to deal with selection bias (Heckman, 1979) stemming from loan application review. To infer the risk profile of borrowers, we estimate the probability of loan default using repayment data of the MFI. To deal with non-random assignment to a business training course, we introduce instruments in both the loan default equation and business training equation. To deal with selection bias, we introduce a loan approval equation in our econometric model using data on loan applicants. We end up with three equations for loan default, business training, and loan approval, respectively, which we jointly model to increase the efficiency of our estimates using a trivariate probit model. To ensure robustness of the results, we use two alternative models: trivariate mixed (probit and duration) and nested logit.

All three models exhibit a non-monotonic relationship between the probability of assignment to business training and the risk of loan default. More specifically, we find that the probability of being assigned to a training course first increases with borrower risk, before decreasing beyond a certain threshold. Finally, taking into account this non-monotonic pattern, we find a positive impact of business training on loan survival time. This underlying result contributes to the ongoing debate about the positive effects of business training in microfinance (McKenzie and Woodruff, 2014).

Our research relates to three broad strands of literature, namely: informed lending, credit scoring, and the effects of business training on entrepreneurs' outcomes. Our theoretical mechanism is related to the first strand. Within the general framework of an informed principal, Benabou and Tirole (2003b) state that, for its action to have an impact on the agent's behavior, the principal must hold private information relevant to the agent's behavior and the agent must be aware of the principal's information advantage and objectives.³

Benabou and Tirole (2003a) studied various situations where the principal might be better informed than the agent (for example at school, in the labor market, and in the family)

²In the following, we use project risk or borrower risk interchangeably to refer to the global risk profile of a loan, including individual, household, and business characteristics.

³The notion of informed principal goes back to Myerson (1983) and Maskin and Tirole (1990).

and considered the case where help might undermine motivation.⁴ Ishida (2006) showed that promotions in the labor market could be used strategically; and Swank and Visser (2007) pointed out that delegation and increased attention from an informed employer could improve the motivation of an uninformed employee.

When it comes to financial markets, only a few papers have applied the better-informed lender's framework. "Informed lending" was first introduced in Inderst and Mueller (2006), positing that a lender is better informed about the probable profitability of a newly financed project.⁵ Inderst (2008) studied consumer lending with informed lenders making better estimates of default probabilities than borrowers themselves. The author shows that information advantage can lead to overly aggressive lending decisions. Inderst (2008) argued that the assumption of a better-informed lender was plausible in consumer lending since lenders have a store of past experience and operate in the same geographical areas as clients facing similar economic conditions, while households might have a limited understanding of financial products, and not possess any statistically accurate information. This setting is remarkably similar to the microcredit market, where micro-entrepreneurs are borrowing from experienced MFIs to start a business for the first time. We contribute to this strand of literature by adding the behavioral responses of borrowers involving risk-reducing effort. These behavioral responses may also be viewed as a change in the intrinsic motivation of borrowers caused by extrinsic incentives, i.e., the offer of business training (Besley and Ghatak, 2016). They may also be assimilated to the so-called "looking-glass self" mechanism (Cooley, 1902) whereby loan agreements proposed by informed lenders convey information to borrowers about their own project risks.

The second strand focuses on the bank selection problem (Manski, 1989) and credit scoring (Hand and Henley, 1997). Credit scoring models in Boyes, Hoffman, and Low (1989) and Roszbach (2004) are examples of selection models that underline the importance of controlling for bank selection process at the approval stage (Heckman, 1979). Selection models do not impute missing data but, instead, jointly model the probability of loan approval and repayment quality (Chen and Åstebro, 2012). Yet most of the literature on credit scoring uses consumer credit data (Thomas, Oliver, and Hand, 2005). Given that data on business microloan applications to a specific (French) MFI were available, we adopted a selection model approach and jointly estimated loan approval by the MFI and loan repayment (Bourlès and Cozarenco, 2018). Importantly, the structure of our data set required that a third process be added to the estimate, namely, assignment to a business training course. Therefore, our main contribution to the credit score literature consists in the development of a trivariate approach.

Finally, we contribute to the literature addressing the effects of business training on entrepreneurial performance. The most common forms of business training aim to help potential entrepreneurs to start new firms, and existing firms to earn more revenue. Indeed, aid agencies and governments spend more than one billion US\$ on business training every

⁴Other situations where, in general, help may be detrimental to the agent were presented by Gilbert and Silvera (1996). Using various experiments, the authors showed that help could be used to undermine the beliefs of the agents, who might attribute successful performance to help rather than to the performer's abilities.

⁵Inderst and Mueller (2006) studied security design under informed lending. In a related setting, Axelson (2007) analysed security design in situations where external investors were better informed than the managers of the firm. In the insurance market setting, Villeneuve (2000) analyzed situations where an insurer could evaluate risks better than its customers.

year (McKenzie, Woodruff, Bjorvatn, Bruhn, Cai, Gonzalez-Uribe, Quinn, Sonobe, and Valdivia, 2021). In a recent meta-analysis, McKenzie (2021) found that traditional training programs had a moderate but significant effect on company profits and sales. Most recent studies address the effects of business training in the context of developing countries through experimental techniques (Bruhn, Karlan, and Schoar, 2018). Yet Giorcelli (2019) used a non-experimental approach and found that Italian businesses benefiting from management courses were more likely to survive and experienced higher sales, growth, and productivity compared to their untrained counterparts. Our paper contributes to this literature by using a non-experimental approach to study the behavioral responses to training and confirms its positive effect on the survival time of microloans.

Regarding microfinance more specifically, studies are agnostic about the efficiency of business training (see Garcia and Lensink, 2019; McKenzie and Woodruff, 2014, for a comprehensive review). The lion's share of the existing studies addresses the effects of business training through experimental data (Bulte, Lensink, and Vu, 2017; Sayinzoga, Bulte, and Lensink, 2016; Berge, Bjorvatn, and Tungodden, 2015; Valdivia, 2015; Crépon, Duflo, Huillery, Parienté, and Seban, 2014; De Mel, McKenzie, and Woodruff, 2014; Giné and Mansuri, 2014; Bruhn and Zia, 2013; Karlan and Zinman, 2011) and only a few use non-experimental techniques (Biosca, Lenton, and Mosley, 2014b; Evans, 2011; Edgcomb, 2002). Overall, the results are mixed. On the one hand, in non-experimental contexts, assignment to business training is endogenous. On the other hand, it is widely acknowledged that help does trigger behavioral reactions (Gilbert and Silvera, 1996; Benabou and Tirole, 2003a). By the same token, business training can generate behavioral responses by entrepreneurs. While the first issue can be mitigated by using experimental techniques, this approach generally ignores behavioral reactions intertwined with the direct impact of training. Furthermore, experimental designs are likely to cancel out behavioral responses if participants are aware of the random allocation, which should be the case owing to informed consent requirements (Bédécarrats, Guérin, and Roubaud, 2020, pp. 13–19).

Our contribution to this last strand is threefold. First, in contrast to experimental studies, we account for the behavioral implications of business training stemming from the superior information that MFIs have about their borrower risk profiles. Second, most of the existing studies have focused on the impact of business training on business outcomes, knowledge, and practices rather than on loan repayment, which is our main interest.⁶ One exception is Karlan and Valdivia (2011), who found that access to training (marginally) increased the probability of perfect repayment to the MFI.⁷ Finally, most of the literature deals with developing countries, while we used data concerning a French MFI, similarly to Crépon, Duflo, Huillery, Parienté, and Seban (2014).⁸

The remainder of the paper is structured as follows. Theoretical mechanisms rationalizing business training provision within the informed-lender framework are discussed in

⁶There are two main reasons for this. First, some of the studies focused on the impact of business training on beneficiaries who were not necessarily microloan recipients. Second, in developing countries repayment rates are very high in microfinance (Armendariz and Morduch, 2010), so there is little heterogeneity in terms of loan default.

⁷Similarly, Giné and Mansuri (2014) found that training had no significant impact on the repayment rates of microfinance clients in rural Pakistan.

⁸As regards studies in developed countries, one should also mention Edgcomb (2002) and Evans (2011), who mainly focus on the United States.

Section 2. We then present the microfinance institution that provided the data, followed by the data set, in Section 3. The econometric strategy is described in Section 4 and empirical results are outlined in Section 5. Section 6 presents further analyses and robustness checks. Finally, Section 7 concludes.

2. THEORETICAL MECHANISMS

We first sketch theoretical mechanisms, whereby (1) business training provision is likely to trigger a behavioral response if the lender is better informed than the borrower, and (2) this may affect the MFI's decision regarding training provision. Our reasoning is based on the psychological or behavioral effect that assignment to business training can have on borrowers unaware of their own risk profiles (or types). This effect is likely to occur if the principal (here the MFI) is better informed than the agent (here the borrower) on the latter's characteristics (the quality of his/her project).⁹

This is a typical situation in the microcredit market, where MFIs generally finance first-time micro-entrepreneurs who need financial backing to start a business but usually lack the necessary know-how. Thus, microfinance institutions, thanks to their experience, may well be better informed than micro-entrepreneurs themselves about the potential of a given project. In such a case, the loan agreement drawn by a given MFI can provide the borrower with information about his/her own project, thereby shaping his/her beliefs and behavior.

In the following, we will consider a hypothetical MFI providing microcredit to entrepreneurial projects. All microloans share standard characteristics: no collateral is required and the same interest rate is applied to all borrowers. Within the loan agreements, assignment to a business training course is the only source of heterogeneity. Here, our aim is to highlight how, in a simple setting, informed lending may generate a non-monotonic relationship between borrower risk and assignment to training. In particular, we abstract away from other information asymmetries likely to occur in the lending relationship.¹⁰

Consider an agent, or borrower, who has a project in need of financing. He/she has neither collateral nor is able to make a personal financial contribution to the project and thus needs to borrow the totality of the funds from the MFI. We divide the funding process into two stages: (i) the MFI decides to reject or approve a loan, and (ii) it decides to allocate training to some of the approved projects. During the loan application review, the MFI already takes into account a potential subsequent assignment to business training.

If launched, the project will generate a return in the case of success and nothing in the case of failure. In the first case, the MFI will demand a return (through a fixed interest rate) but in the second case will receive nothing. We assume that the probability of project success will depend on borrower type, borrower effort, and level of business training provided by the MFI, and will increase with these three parameters.

Borrower type represents the intrinsic probability of success depending on borrower and project characteristics, but excluding the effects of business training and effort. Following the literature on help and effort (see e.g., Benabou and Tirole, 2003a), we assume that

⁹See Benabou and Tirole (2003b) for similar settings in other markets.

¹⁰In reality, the informational advantage enjoyed by the MFI regarding the business environment—through its specialization (Paravisini, Rappoport, and Schnabl, 2015), its experience (Inderst and Mueller, 2006), or its statistical model (Treacy and Carey, 2000)—is likely to coexist with more classical asymmetric information to the benefit of the borrower.

the efficiency of business training decreases with borrower type.¹¹ To simplify our setting further, we assume that business training costs are only borne by the MFI; and that the cost of effort (borne by the borrower) is type-dependent.¹² We more specifically focus on the (psychological) cost of effort decreasing with borrower type, leading to a greater incentive to exert an effort for the stronger type.

Regarding the MFI's objective, we assume that once a borrower has been issued a loan, the MFI will either seek to maximize profit or minimize loss on this loan. We discuss the overall objective of the MFI and how it impacts the selection stage in the Appendix (end of Section 8.1). We follow the standard approach in banking modeling by assuming that the MFI is risk neutral and, as is often assumed in principal-agent settings, that the borrower is also risk neutral.¹³

Our aim is to analyze the effect of informed lending on business training provision. In this setting, the level of business training selected by the MFI conveys information about borrower type and might influence the borrower's behavior. In other words, by observing the level of business training, borrowers may form a belief about their own type that might lead them to exert some amount of effort. When providing business training, the MFI internalizes this mechanism, which shapes its profit through the efforts of borrowers. We show that this mechanism may give rise to a non-monotonic relationship between business training provision and borrower type.

We formally illustrate this theoretical argument in the Appendix (see Section 8.1) through a simple discrete version of the model, with two levels of effort and business training and three types of borrowers, namely, weak (W), medium (M), and strong (S). We then show that a better-informed lender will choose to train only medium-type borrowers, in settings where the efficiency of the training (and effort) technology would lead to training both weak and medium types in the absence of asymmetric information.¹⁴

If the MFI is better informed than its clients, contract terms such as assignment to a business training course (or not) convey information to the borrower, who may take note of the MFI's decision and, as a result, form beliefs about his/her own borrower type.

¹¹We borrow this standard theoretical assumption from Benabou and Tirole (2003a). In their setting, training "makes more of a difference for weak agents than for strong ones", and basically constitutes "bad news". Reverting this assumption would make it "good news" and generate the opposite psychological effect to the one studied here, potentially leading to the opposite non-monotonic relationship between borrower risk and assignment to business training. The empirical microfinance literature has not reached a consensus concerning the heterogeneity of training impact (McKenzie and Woodruff, 2014). Yet some studies find that training has a stronger effect on entrepreneurs who have received a less formal education (Bjorvatn and Tungodden, 2010) and for individuals taking out smaller loans (who are also riskier individuals, Berge and Garcia Pires, 2021), making our assumption on the decreasing efficiency of business training with borrower type plausible.

¹²Our results easily extend to situations in which the selected borrowers bear part of the cost of training (e.g., through opportunity cost), as long as this cost is type-independent. A proper examination of this case would, however, imply verifying participation constraints for the borrowers, which are automatically verified in our setting. We would then abstract away from the cost of training from the borrower's point of view and focus on the cost borne by the MFI (be it an administrative or an opportunity cost, through file filling for example).

¹³Our results extend to risk-averse borrowers if effort carries a utility cost and utility in case of failure is nil.

¹⁴Such a non-monotonic relationship between business training and borrower type could also arise under perfect information if one assumed training to be highly efficient for the medium type but not for strong or weak types. This, however, seems unlikely and would contrast with standard assumptions in the literature.

We identify the conditions under which the MFI only trains medium-type borrowers at equilibrium.¹⁵ Borrowers observing that they have not been assigned to a training may infer that they either belong to the weak or strong type. Such an equilibrium occurs if training and effort technologies are such that:

(i) borrowers who believe that they belong to either the weak or strong type have an incentive to exert an effort if they are not provided with any training, and

(ii) the MFI prefers to train medium-type borrowers, although they do not exert any effort, rather than weak-type borrowers, in order to incentivize the latter to make an effort (see Section 8.1 for the formal condition). These conditions imply in particular that the efficiency of effort, when no training is provided, is higher for weak-type than for medium-type borrowers. The effort of weak-type borrowers is then crucial for the MFI, which uses its informational advantage to incentivize it.¹⁶

Importantly, this mechanism holds both for for-profit and not-for-profit MFIs.¹⁷ The objective of the MFI shapes the pool of selected borrowers, but is unlikely to impact training decisions. Once a borrower's loan application is approved, one can reasonably assume that the aim of the MFI will be to maximize the expected profits or, equivalently, minimize the expected loss. We show in the Appendix that—by taking into account subsequent assignments to business training—lender's information advantage can lead to higher approval rates of weak-type borrowers, both in the case of for-profit and not-for-profit MFIs.¹⁸ This echoes previous findings suggesting that business training leads to an increased MFI outreach (Bourlès and Cozarenco, 2014).

Our theoretical analysis suggests that the existence of behavioral responses by borrowers leads informed MFIs to tailor their business training provision to borrower risk in a non-monotonic way. This leads us to formulate the following testable hypothesis:

H1. The relationship between the probability of assignment to business training and borrower risk is non-monotonic: It first increases with the borrower risk level and then, beyond a certain threshold, decreases.

H1 materializes the effect of informed lending on business training in the microfinance setting. By controlling for borrower selection, assignment to training, and behavioral responses, we will also be able to assess the impact of business training on loan repayment rates. To test this hypothesis and its underlying mechanisms, we used a hand-collected set of data originating from a French MFI; the institutional background and data are presented in the next section.

¹⁵ As explained in Section 8.1, we focus on the unique non-pooling Perfect Bayesian Equilibrium.

¹⁶ These situations in which effort exerted by the most risky borrowers is crucial for the lender seem to fit in well with the microcredit setting described above (i.e., mostly unemployed borrowers, with a lower education level, who start a business for the first time).

¹⁷ We do not require profits to be positive at equilibrium in the formal model.

¹⁸ According to Cull, Demirgüç-Kunt, and Morduch (2018), for-profit MFIs make up 38% of microfinance institutions worldwide. De Quidt, Fetzer, and Ghatak (2018) point out that MFIs worldwide tend to shift from non-profit organisations to for-profit institutions.

3. INSTITUTIONAL BACKGROUND AND DATA

3.1. Institutional background

To investigate assignment to business training courses, we hand-collected data on loan applicants and borrowers at *Contraction de Crédit Accompagnement Solidarité* (Créa-Sol), a French MFI. The data covers the period from May 2008 to May 2011. Créa-Sol was set up in 2006 in the south of France as an NGO on the initiative of Caisse d'Épargne Provence-Alpes-Corse, a regional savings bank, to comply with the legal framework requiring banks to pursue social and local economy projects. The MFI targets individuals who have difficulty accessing the financial services of mainstream banks, through individual liability, in contrast to the joint liability lending methodology (De Quidt, Fetzer, and Ghatak, 2016). Its mission is "*to revitalize the economy of the territories, by creating local economic activity that cannot be relocated and generating new jobs*".¹⁹ Therefore, most of the clients are (long-term) unemployed, have a low level of education and income, and are starting a business for the first time.²⁰ Loans may be taken out for a business start-up, buy-out or development (for businesses younger than three years) in order to escape unemployment and/or poverty.

Yet the vast majority of loans issued during the sample period were for a business start-up or buy-out, rather than for business development. The average loan amount was EUR 8,900, the average interest rate 4.2%,²¹ with a mean maturity of 52 months. The MFI does not require any collateral or guarantees from clients, which means that the total pool of applicants is considered "too risky" by most commercial banks.

Créa-Sol's selection process consists of two stages (see Figure 1). First, the applicant contacts the MFI to discuss the financing of an entrepreneurial project. A face-to-face meeting with a loan officer takes place to examine the maturity of the project. If it proves to be mature enough, the loan officer prepares a formal application file. Second, the loan officer examines the borrower's profile, including factors such as educational background, occupation, skills, and motivation, and also requests some financial information—but uses this in a flexible way. Then, the officer presents the application file to the lending committee and makes a recommendation, which can either be approval, with or without business training, or rejection of the loan request. Loan officers internalize the subsequent training provision when they prepare their recommendation. Therefore, training is a risk-mitigating strategy implemented by the microfinance institution.²² The credit committee generally follows loan officers' recommendation but has the final say.

Each individual may only apply once for a microloan, for the MFI aims to facilitate the graduation of all its clients to a mainstream bank after their first microloan. Créa-Sol is highly active in business training. More generally in Europe, non-financial services are an important feature of MFIs, which play a counseling and support role (Brana, 2013). In most cases, business training is provided free of charge to clients. For this reason, to cut their costs, MFIs often form partnerships with other NGOs, which are subsidized

¹⁹See <http://www.crea-sol.fr/qui-sommes-nous/> accessed on February 16, 2022.

²⁰We did not have access to any information about their past jobs, loan applications, or training.

²¹The interest rate was set at 4% per year at the beginning of the period of study and reached 4.5% at the end. The interest rate was fixed and hence did not depend on borrower characteristics, which is a common practice in microfinance (Agier and Szafarz, 2013).

²²To our best knowledge business training was generally proposed by the MFI, rather than triggered at the borrower's request.

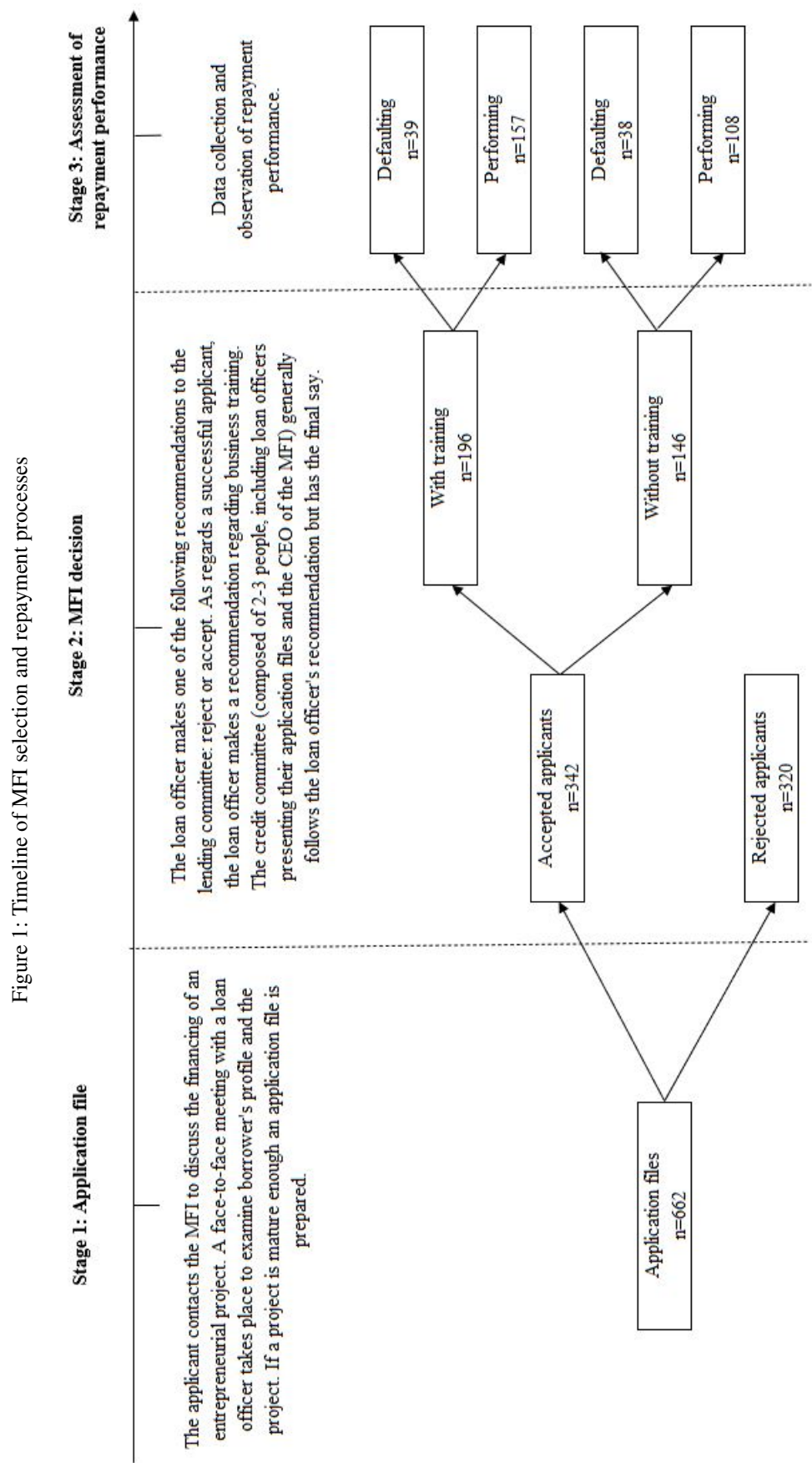
institutions (Bourlès and Cozarenco, 2014) and Créa-Sol has followed this model.²³ If a borrower is assigned to a business training course by Créa-Sol, he/she has to attend it. Yet we could not ascertain whether clients had actually attended all sessions because we only received information about assignments to these courses.²⁴ To our knowledge, Créa-Sol borrowers did not receive any training other than that mentioned in the data set.

Business training can take various forms. In the case of a business start-up, training consists of support with developing a business plan and formalizing the project, and lasts for a minimum of four months. As regards existing businesses, it consists of business development services, can last for up to three years, and is offered either to individuals or to groups. It addresses various topics, such as: product diversification, communication strategy, marketing, access to funding, technical assistance, taxes, social and legal advice, and so on. Business development services are generally provided by accountants, lawyers, tax specialists, notaries, IT consultants, and communication experts.

Finally, loan officers monitor the loan repayment performance of borrowers. Créa-Sol follows a standard approach to portfolio quality assessment in microfinance, whereby it writes off all loans involving three or more consecutive delayed payments. We observed the repayment behavior of each client, including the number and dates of unpaid installments. The next subsection provides the descriptive statistics for each of the three processes: loan application review, business training provision, and repayment performance.

²³ According to Botti, Dagradi, and Torre (2016), 87% of Western European MFIs providing non-financial services externalize them to third parties.

²⁴ Drop-out rates from training programs have hardly been studied in the literature, mainly owing to data limitations. The French General Inspectorate of Finance estimates that the three-year drop-out rate from the NACRE (*Nouvel Accompagnement pour la Création ou la Reprise d'Entreprise*) training program is 62% (Schechter, Toussain, Thomas, Abrossimov, and Colas, 2013), while German training programs have an average drop-out rate of 20% (Paul, 2015). High drop-out rates from a training program might mitigate its impact.



3.2. Data

Our data set was built upon three stages (i.e., application file, MFI decision, and assessment of repayment performance, see Figure 1). The first two stages consist of Créa-Sol selection process and the last stage consists of the observation of the loan repayment.

Summary statistics in Table I provide information on the following items: total sample of applicants; approved and rejected applications (Panel A); borrowers who received business training and those who did not (Panel B); and defaulting and performing borrowers (Panel C), along with t-tests or χ^2 to compare different group means. The first column in Table I shows that out of 662 applicants, 51% were granted a microloan. Panel A shows that among successful applicants, 23% defaulted. By "defaulting", we mean borrowers with three or more delayed payments in their credit history at Créa-Sol.²⁵ Delayed payments 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 what was actually registered by Créa-Sol.

In addition, Panel A shows that individuals who are long-term unemployed, have a low household income, can only make a small personal financial contribution to the project, or manage businesses in the food and accommodation sectors, are more likely to see their applications rejected by the MFI. These descriptive statistics corroborate the fact that selection bias is real and that we need to control for it in the regression analysis. In contrast, gender, educational achievements, marital status, and business assets do not seem to play a decisive role during the loan application review.

Panel B splits the borrowers into business training beneficiaries and non-beneficiaries. Overall, 55% of clients receive some business training.²⁶ Of these, 20% are defaulting clients, against 26% of clients not receiving business training. However, this difference is not significant. These preliminary descriptive statistics suggest that trained beneficiaries are not subsequently riskier than non-beneficiaries. This evidence reflects two possible scenarios: (i) either training is targeted toward individuals initially considered to be high-risk and is highly efficient (given that, with hindsight, borrowers who have completed a training course are not riskier than borrowers who have not) or (ii) training is not targeted exclusively toward high-risk borrowers. As pointed out above, existing studies fail to corroborate the first scenario (i.e., business training is highly efficient). This lends credence to the second scenario, where business training is not necessarily allocated to the riskiest borrowers.

The individual characteristics of business training beneficiaries do not appear to differ much from those of non-beneficiaries. Nevertheless, a few differences do deserve to be mentioned. Business training beneficiaries have higher household incomes and their

²⁵This percentage might appear particularly high in the microfinance context. Indeed, D'Espallier, Guérin, and Mersland (2011) report 6% of the total loan portfolio as more than 30 days overdue (PaR30) and only 1% of loans as written-off in a study of 350 MFIs in 70 countries. However, for MFIs in Western Europe the PaR30 is 13.4% and the write-off ratio is 5.6% according to Botti, Dagradi, and Torre (2016), comparable to the figures reported in our study.

²⁶Assignment to a training program may be interpreted as "treatment" and thus borrowers can be divided into a treated and a control group. From this perspective, our paper fits into the literature studying treatment effects. Nevertheless, in our case treatment is obviously not randomly assigned.

businesses have higher asset levels. Furthermore, they are more likely to have made other applications for loans and to have been granted honor loans,²⁷ which is consistent with the microcredit setup in France, where NGOs providing training courses in partnership with MFIs also provide honor loans. The *other applications* variable often includes ongoing applications for an *honor loan*. Hence there is a direct link between these 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. Furthermore, borrowers sent by a mainstream bank are less likely to be offered a training course.

Finally, Panel C splits the sample into defaulting and performing loans. Half of the defaulting loan recipients, versus 59% of performing loan recipients, were assigned to a training program, but this difference is not significant. As Table I illustrates, there are significant differences between defaulting and performing clients. Defaulting clients are more likely to be male, single, less educated, have lower levels of income and personal investment,²⁸ and fewer assets. All these variables are controlled for in the risk analysis outlined in the next section along with our econometric strategy.

²⁷ 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.

²⁸ *Low personal investment* is a dummy taking the value of 1 if the applicant's personal financial contribution to the project is lower than 5% of the project size. We used this cut-off because it was the lowest available in our data after *no personal investment*, and very few applicants provided no personal investment at all.

TABLE I
SUMMARY STATISTICS

Variables	Total sample (n=662) (1)	Panel A: Loan application review			Panel B: Business training			Panel C: Repayment performance		
		Granted (n=342) (2)	Rejected (n=320) (3)	t-test ^a / Chi ² (4)	Training (n=196) (5)	No Training (n=146) (6)	t-test ^a / Chi ² (7)	Defaulting (n=77) (8)	Performing (n=265) (9)	t-test ^a / Chi ² (10)
Approval rate	0.51 (0.50)									
Defaulting (dummy)		0.23 (0.42)			0.20 (0.40)	0.26 (0.44)	1.80			
Business training (dummy)		0.57 (0.50)						0.51 (0.50)	0.59 (0.49)	1.80
Individual characteristics										
Male (dummy)	0.62 (0.48)	0.61 (0.49)	0.64 (0.48)	0.72	0.62 (0.49)	0.60 (0.49)	0.16	0.74 (0.44)	0.57 (0.50)	7.27***
Education (# educational qualifications)	1.90 (1.36)	1.91 (1.37)	1.88 (1.36)	-0.31	1.91 (1.42)	1.92 (1.31)	0.06	1.47 (1.18)	2.04 (1.40)	3.28***
Single (dummy)	0.55 (0.50)	0.53 (0.50)	0.58 (0.49)	1.26	0.50 (0.50)	0.58 (0.50)	1.91	0.62 (0.49)	0.51 (0.50)	3.32*
Unemployed for over 12 months (dummy)	0.39 (0.49)	0.34 (0.47)	0.45 (0.50)	8.93***	0.37 (0.48)	0.29 (0.45)	2.69	0.40 (0.49)	0.32 (0.47)	1.96
Household characteristics										
Household income (in thousand EUR)	1.38 (1.14)	1.49 (1.16)	1.27 (1.11)	-2.43**	1.61 (1.23)	1.32 (1.04)	-2.24**	1.12 (0.80)	1.59 (1.23)	3.15***
Household expenses (in thousand EUR)	0.46 (0.50)	0.45 (0.49)	0.47 (0.50)	0.61	0.47 (0.52)	0.42 (0.45)	-0.83	0.47 (0.43)	0.44 (0.51)	-0.39
Business characteristics										
Low personal investment (dummy)	0.29 (0.45)	0.25 (0.44)	0.33 (0.47)	4.53**	0.26 (0.44)	0.25 (0.44)	-0.04	0.39 (0.49)	0.22 (0.41)	9.58***
Assets (in thousand EUR)	18.20 (23.62)	19.24 (25.95)	17.10 (20.86)	-1.17	21.52 (30.02)	16.17 (18.83)	-1.90*	12.28 (9.44)	21.26 (28.74)	2.70***
Food and accommodation sectors (dummy)	0.12 (0.33)	0.10 (0.30)	0.15 (0.36)	3.15*	0.09 (0.28)	0.11 (0.33)	0.14	0.09 (0.29)	0.11 (0.31)	0.14
Gross margin(EUR)/Sales(EUR)	0.75 (0.20)	0.74 (0.20)	0.77 (0.20)	1.92*	0.74 (0.20)	0.74 (0.20)	0.11	0.71 (0.21)	0.74 (0.20)	1.28
Instruments for business training										
Other applications (dummy)		0.64 (0.03)	0.59 (0.03)	2.43	0.82 (0.38)	0.39 (0.49)	-9.12***	0.51 (0.06)	0.67 (0.03)	7.37***
Honor loan (dummy)		0.49 (0.03)	0.47 (0.03)	0.47	0.65 (0.48)	0.29 (0.45)	-6.99***	0.43 (0.06)	0.51 (0.03)	1.63
Sent by a mainstream bank (dummy)		0.19 (0.02)	0.14 (0.02)	3.03*	0.12 (0.33)	0.28 (0.45)	3.79***	0.14 (0.04)	0.20 (0.02)	1.47

Notes: This table reports the number of observations, mean, and standard deviation in parentheses for the variables used in the empirical analysis. *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively, for the t-test and Chi² test.
^aThe t-test is a two-sample two-sided test for equal means.

4. ECONOMETRIC MODEL

In line with our theoretical reasoning, our empirical strategy addresses two MFI decisions: loan approval/rejection and, for approved borrowers, assignment to a training course. However, one of our main challenges is that we cannot observe borrowers' intrinsic risk, which corresponds to their type in the theoretical model. Therefore, to detect the presence of a potential non-monotonic relationship between the probability of assignment to training and borrower risk (as depicted in H1), we recover the risk associated with each borrower by using loan repayment data provided by the MFI. To do so, our empirical strategy builds upon three simultaneous equations using cross-section data: loan default, assignment to training, and loan approval. We end up with a trivariate probit approach presented at the end of this section together with our identification strategy.

4.1. Risk measurement

We use loan repayment data originating from the MFI to proxy borrower risk. Information about loan repayment allows us to reconstruct the individual intrinsic risk taken into consideration by the MFI thanks to its informational advantage. Our risk metric is deduced from the probability that a borrower will default, estimated by a probit model. Denoting by y_{1i} the dummy variable indicating default, the loan default equation then writes:

$$(1) \quad y_{1i}^* = w_i' \beta_1 + \eta \mathbf{B}_i + \alpha_1 y_{2i} + \epsilon_{1i}, \quad y_{1i} = \begin{cases} 1 & \text{if } y_{1i}^* > 0 \text{ Defaulting} \\ 0 & \text{if } y_{1i}^* \leq 0 \text{ Otherwise} \end{cases}$$

The main risk factors—including the individual, household, and business characteristics presented in Table I—are grouped in the vector w_i . Furthermore, the loan repayment process is also impacted by economic and event factors, i.e., business cycles and business training courses occurring during the start-up phase. For this reason, we also control for business cycles in a vector denoted \mathbf{B}_i which can exogenously impact the riskiness of a project. Business cycle data include quarterly rates of increase in business failures (as a metric of economic health) and in new business start-ups (as a metric of competition) at the time when the loan was granted (as well as one and two quarters later) in the sector of activity of each microenterprise in our sample.²⁹ Including business cycle variables in the default equation also accounts for the consequences of the recent financial crisis, which overlaps with the beginning of our sample period (2008–2011).

Furthermore, loan repayment is observed at the end of the sequence (see Figure 1) and is thus potentially endogenously determined by business training, both directly and indirectly—through borrowers' behavioral reactions to being asked to attend a business training course. We attempt to isolate these two effects. To identify the direct effect of business training, we introduce a dummy variable (y_{2i}) indicating whether a borrower has received business training into the loan default equation. To isolate indirect behavioral effects, we introduce heteroscedasticity linked to individual unobserved heterogeneity and depending on business training in the error term ϵ_{1i} .³⁰

²⁹Indeed, an unfavorable economic environment during the start-up phase can jeopardize a business's chances of survival. Data for business cycles exclusively cover the French south-eastern *Provence-Alpes-Côte d'Azur* Region where the MFI in our study operates. Source: Fiben, Banque de France.

³⁰This approach is similar to Heckman, Pinto, and Savelyev (2013), where treatment indirectly modifies

This empirical strategy allows us to deduce the *Risk* variable used by the MFI during the assignment to training process from Equation (1), for each borrower. Given the estimates of the effects of individual, household, and business characteristics, we use the risk net of potential direct and indirect effects of business training and net of business cycle influence as a proxy for borrowers' intrinsic risk:³¹

$$(2) \quad Risk = \Phi(w_i' \beta_1 + v_i)$$

where $\Phi(\cdot)$ is the normal cumulative distribution function and v_i is an individual unobserved heterogeneity factor, which is one of the components of the error term ϵ_{1i} in the Equation (1). We will detail the structure of ϵ_{1i} in Section 4.4. We use loan survival time to build an alternative measure of borrower risk in a robustness check (see Section 6.1).

4.2. Business training provision

According to our theoretical model, through behavioral responses by borrowers, informed lending can lead to a non-monotonic relationship between the probability of assignment to a business training course and borrowers' intrinsic risk as assessed by the MFI. According to H1, the probability of assignment to training first increases with the borrower risk level and then, beyond a certain threshold, decreases. To test for H1, we control for *Risk* and *Risk*² in the business training equation. This allows us to capture the simplest form of non-monotonicity. Recalling that y_{2i} is the dummy variable indicating whether borrower i has been offered any training, the business training equation writes:

$$(3) \quad y_{2i}^* = x_i' \beta_2 + \lambda_1 Risk + \lambda_2 Risk^2 + \epsilon_{2i}, \quad y_{2i} = \begin{cases} 1 & \text{if } y_{2i}^* > 0 \\ 0 & \text{if } y_{2i}^* \leq 0 \end{cases} \begin{matrix} \text{Business training} \\ \text{Otherwise} \end{matrix}$$

If H1 is verified, we expect $\hat{\lambda}_1$ to be significantly positive and $\hat{\lambda}_2$ to be significantly negative. x_i is a vector of variables specific to the business training decision (and it does not include any variables in w_i); it is composed of the *honor loan*, *other applications* and *sent by a mainstream bank* dummies. These variables have a direct link to assignment to training. Indeed, as outlined in Subsection 3.2, in France business training is not directly provided by MFIs since it is costly and requires subsidies (de Hoop, Friedman, Kandpal, and Rosati, 2019; Bourlès and Cozarenco, 2014).

4.3. Controlling for selection in loan application review

Borrowers who receive a loan from the MFI are non-randomly selected from the pool of applicants. Hence repayment performance and assignment to training are plagued with selection bias. The advantage of our data is that it provides information both on applicants and borrowers. Therefore, we can use data on loan applications to correct for this bias by introducing a loan approval equation based on the loan application review process, in the

the outcome variable in a childhood program through unobserved skills.

³¹By "intrinsic risk" we mean the probability of defaulting "cleansed" of the direct effect of business training, indirect behavioral effects, and business cycle effects.

spirit of Heckman (1979), which writes as follows:

$$(4) \quad y_{3i}^* = w_i' \beta_3 + \eta \mathbf{B}_{0i} + \epsilon_{3i} \quad y_{3i} = \begin{cases} 1 & \text{if } y_{3i}^* > 0 \text{ Approval} \\ 0 & \text{if } y_{3i}^* \leq 0 \text{ Otherwise} \end{cases}$$

where y_{3i} is a dummy variable taking the value of one for approved applications and zero for rejected ones. We use the same explanatory variables included in vector w_i , as in the risk equation, as suggested by Roszbach (2004). We moreover introduce business cycle variables (\mathbf{B}_{0i}) into the approval equation; these may impact the MFI's decision to grant the loan or not. \mathbf{B}_{0i} is a vector including the rate of increase in business failures and new business start-ups in the sector of enterprise i at the time of loan approval, as well as one quarter and two quarters before loan approval.³²

We jointly model Equations (1), (3), and (4) in a trivariate probit model using the identification strategy outlined in Section 4.4.

4.4. Trivariate probit model and identification

Our empirical strategy allows us to deal with the three main limitations stemming from our data set. First, we do not have the same set of information as the MFI. Indeed, in addition to observable characteristics presented in Table 1, the face-to-face meetings allow the MFI to acquire “soft” information about applicants (motivation, entrepreneurial spirit, personality, etc.), which remains unobserved by the econometrician. Second, in line with our theoretical model, business training provision may impact the behavior of borrowers and, thereby, indirectly affect their risk level. Finally, our study is purposely non-experimental, therefore we need to address the endogeneity of non-random assignment to business training to identify its impact on borrower repayment performance. We describe how we deal with each of these limitations in this section.

To account for a possible correlation between the two MFI decisions (approval/rejection and business training) and repayment performance, we use a trivariate model that imposes a linear factor model on unobservables. In microeconomic analyses (see, for example, Abbring and Heckman, 2007), linear factor models are often used to model unobserved heterogeneity and dependence among different processes in a flexible and parsimonious way. We follow Aakvik, Heckman, and Vytlacil (2005) and choose the one-factor structure with a low dimensional set of factors generating dependence across MFI decisions and borrower outcomes:

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

where the components $\epsilon_{1i}^0, \epsilon_{2i}^0, \epsilon_{3i}^0$ are independent idiosyncratic parts of the error terms. Each is assumed to follow a normal distribution $\mathcal{N}(0, 1)$ and to be independent of the covariates. 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 and of the covariates in the three equations. This unobserved individual heterogeneity

³²In the risk equation, business cycles were considered at the beginning of the loan (as well as one and two quarters later), whereas in the approval equation, business cycles were considered at the time point of approval, which did not necessarily coincide with the beginning of the loan. There was generally little overlap between business cycle variables in the approval and risk equations.

allows us to take into account unobserved “soft” information about borrowers (motivation, skills, personality, etc.) collected by the MFI during face-to-face meetings, but unobserved by the econometrician. These factors drive borrowers’ behavior (for instance, through effort devoted to the business). Thus, this error structure allows us to address the first limitation of our data set.

Attached to v_i , the scedastic function $\rho_{1i} \equiv \rho_1 \exp(\alpha_2 y_{2i} + \delta \text{Education}_i)$ in the error term ϵ_{1i} represents uncertainty driven by borrower behavioral effects. It allows us to control for the indirect effect of business training and, therefore, addresses the second limitation of our data set. In the scedastic function, business training indirectly impacts the probability of default through α_2 . We moreover assume that the behavioral effect depends on the borrower’s level of education (or skills) through the coefficient δ , which also represents the indirect effect of education on the probability of default. The parameters ρ_1 , ρ_2 and ρ_3 are free factor loadings that should be estimated. For identification reasons, we impose $\rho_1 = 1$. We estimate the parameters using the maximum likelihood.

The identification of the effect of business training on borrower risk is a challenging task, owing to endogeneity. Indeed, business training provision and risk profile can co-vary with each other and be determined by unobserved heterogeneity. In particular, business training can affect the risk of default by borrowers. Our purpose being to test for a non-linear relationship between business training provision and borrower risk, business training is non-randomly assigned and our data is purposely non-experimental. Our econometric model is specified by a triangular system of two equations with binary endogenous variables—default and business training, the latter explaining the former. We use identification results by Mourifié and Méango (2014) and Han and Vytlačil (2017) for this class of bivariate probit models and address endogeneity using the instrumental variables approach to ensure identification.³³

To do so, we rely on x_i , the vector of variables specific to the business training decision in Equation (3). These variables are the *honor loan*, *other applications* and *sent by a mainstream bank* dummies. Generally, non-financial services are provided by partner NGOs that also offer honor loans subsidized by the French government. Importantly, the application for an honor loan is subject to some light screening by partner NGOs and is unlikely to have any repercussions on microloan repayment. *Other applications* include ongoing applications for an honor loan or subsidized funding from French public authorities, that generally conduct lighter screening than the MFI. Altogether, these loans fulfill the same purpose as microloans: They are contracted to finance business start-up or development. Therefore, they are unlikely to be used to repay an outstanding loan from an MFI. Finally, applicants sent by mainstream banks generally do not have an ongoing relationship with NGOs providing non-financial services; therefore, they are less likely to be assigned to a business training course.³⁴

MFIs are institutions whose mission is to serve people who are rejected or underserved

³³The necessary identification condition is satisfied by a simple count: The number of non-redundant informative probabilities in the model must be as large as the number of unknown parameters. Given that this is a system of non-linear equations, Mourifié and Méango (2014) show that by using as many equations as there are parameters, there can be several solutions in a bivariate probit model with common regressors. The presence of instruments excluded from the loan default equation then ensures identification.

³⁴Most of the clients were sent by the Caisse d’Epargne Provence-Alpes-Corse, the bank that initiated the MFI in our study.

by mainstream banks. Obviously, clients sent by these banks are considered too risky for them. However, these clients are unlikely to differ in terms of their repayment performance from other applicants to the MFI for two reasons. First, all applicants (not only those sent by a bank) would prefer to be financed by mainstream banks, since their loans are larger, interest rates are in general lower, and there is no requirement to attend training sessions. Second, self-selection of least-risky applicants who decide to apply to a mainstream bank first is unlikely. Microfinance is a new industry in Europe (Cozarenco and Szafarz, 2020) and traditional banks are still perceived as the main providers of business funding. Hence applicants sent by mainstream banks are unlikely to be safer than other applicants.

Given the direct link between the three variables and the likelihood of being assigned to a business training course, we use these variables as instruments in the business training equation to ensure identification. To test the validity of exclusion restrictions, we proceed in two steps. First, we follow Delis, Hasan, Iosifidi, and Ongena (2022) and include the three instruments, at first separately and then concomitantly, in the approval and risk equations, respectively. Delis, Hasan, Iosifidi, and Ongena (2022) argue that the premise for the choice of instrumental variables (IVs) is that they do not directly affect the main outcome variable. By using our IVs directly in Equations (1) and (4), we show that this is the case (see results in Table VIII of Appendix 8.4). In contrast, as we will see in the next section, these variables strongly correlate with the business training dummy. Second, we use classical approaches within a bivariate framework using 2SLS and Poisson regression models (see results in Table IX of Appendix 8.4).

The presence of business cycle variables B_i in the risk equation further ensures identification of our model: They cannot impact assignment to training courses since they occur after the MFI's decision regarding training. Similarly, business cycle variables B_{0i} in the selection equation occurring before loan approval address identification of the endogenous selection equation. These business cycles variables should determine selection but not the future default outcome.³⁵ In the next section, we present our findings.

³⁵In our model, the loan approval equation is only used to control for selection bias in the repayment performance and business training processes, in the spirit of Heckman (1979). One could consider a more general structural model where the MFI's approval/rejection decision is determined by *Risk* predicted by Equation (2). Yet building such a general model is challenging and goes beyond the scope of our study. The identification of our endogenous selection equation is achieved through the presence of business cycles variables at the time and just before the approval decision.

5. ECONOMETRIC RESULTS

Econometric results are reported in two steps. First, we present our main findings addressing the relationship between business training provision and borrower risk by testing for H1 in the business training equation (3). Second, we contribute to the ongoing debate concerning the effect of business training, using the results of the estimate of the loan default equation (1). We also briefly discuss the results of the loan approval equation (4). The results of the estimates of the coefficients of the trivariate probit model and their marginal effects are reported in Table II.

5.1. Business training provision and borrower risk

The estimation of the business training equation in column (4) in Table II shows that both $\hat{\lambda}_1$ and $\hat{\lambda}_2$ are significant at the 10% and 1% levels, respectively. The opposite signs indicate that the probability of receiving business training first increases with the borrower risk level and then, beyond a certain threshold, decreases. Using the estimates in column (4), we can compute the threshold beyond which the probability of receiving business training begins to decrease with risk. To this end, we use the derivative:

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

where $\phi(\cdot)$ is a normal density that 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 0.38 and negative otherwise according to the estimates of the trivariate probit model. In our data set, the estimated risk of 81% of borrowers is lower than 0.38 and for 19% it is higher.

Figure 2 illustrates the relationship between the predicted borrower risk (on the horizontal axis) and the predicted probability of business training provision (on the vertical axis). Each point on the inverted U-shaped curve corresponds to one individual prediction and the upper and lower bounds represent the 95% confidence intervals. Figure 2 confirms the non-monotonic relationship between the intrinsic risk of a borrower and his/her likelihood to receive business training. For borrowers whose predicted probability of default is lower than 0.38, the probability of being assigned to a business training course increases with their risk. In contrast, for borrowers with a predicted probability of default higher than this threshold, the probability of being assigned to a business training course decreases. The 95% confidence interval shows that this relationship is significant. The trivariate probit model validates H1 and confirms the non-linear relationship between assignment to business training and borrower risk in a setting involving a better-informed lender.

In order to better relate our findings to the simple discrete version of our theoretical model, we reproduce this analysis by splitting our sample into three groups of the same size: weak (W), medium (M), and strong (S), to echo the theoretical model. The S group contains borrowers with a predicted risk lower than the 33rd percentile ($Risk < 0.167$); the M group contains borrowers with a predicted risk between the 33rd and 66th percentile ($0.167 \leq Risk < 0.542$); and the W group contains borrowers with a predicted risk higher than the 66th percentile ($Risk \geq 0.542$).

Figure 3 confirms the differences among the three risk groups, as well as the fact that the probability of receiving business training is significantly higher for the M group than for other borrowers. Indeed, we observe no overlap between the predicted probability of receiving business training for riskiest (W) borrowers and M borrowers. The difference

between M and least-risky borrowers (S) is less sharp, but overlaps are concentrated in the extreme quartiles. Still, the difference between W and S-type borrowers is less pronounced, indicating that these borrowers may be pooled together—as in our theoretical model—when it comes to business training provision.

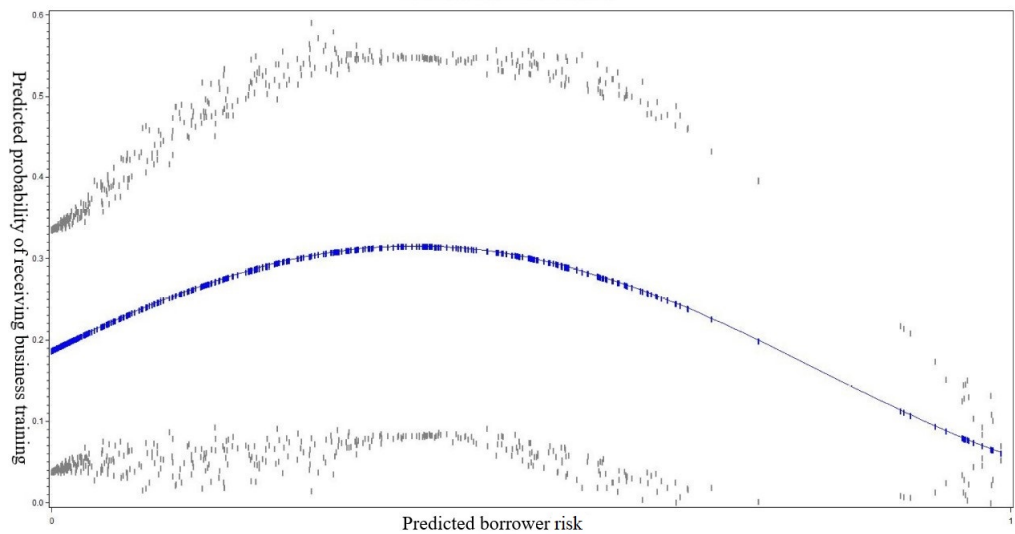
The effects of control variables are strongly significant and in line with expectations outlined in the above discussions. We observe a significant positive relationship between business training and *other applications* and *honor loan*. However, being *sent by a mainstream bank* is negatively associated with the likelihood of receiving business training. $\hat{\rho}_2$ is not significant, suggesting that adding borrower risk to the business training equation is sufficient to control for the interdependence of the two processes and any potential endogeneity.

TABLE II
TRIVARIATE PROBIT MODEL

Dependent variables:	Loan approval			Business training			Loan default		
	Coef (1)	SE (2)	Average marginal effect (3)	Coef (4)	SE (5)	Average marginal effect (6)	Coef (7)	SE (8)	Average marginal effect (9)
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)		0.23			
Honor loan				0.53*** (0.17)		0.08			
Sent by a mainstream bank				-0.57*** (0.19)		-0.03			
$\hat{\rho}_2$				-0.13 (0.31)					
Business training (direct effect)							0.09 (0.49)		0.13
Education (direct effect)							-0.19 (0.14)		-0.03
Male	-0.03 (0.09)		0.00				1.03*** (0.39)		0.12
Unemployed at least 12 months	-0.29 (0.28)		-0.03				0.59** (0.26)		0.04
Single	-0.72** (0.35)		-0.04				0.18 (0.28)		0.02
Household income (in thousand EUR)	0.02 (0.26)		0.00				-0.51** (0.2)		-0.10
Household expenses (in thousand EUR)	0.22 (0.14)		0.03				1.16** (0.45)		0.22
Low personal investment	-0.43 (0.29)		-0.07				0.65** (0.31)		0.04
Assets	-0.46 (0.3)		-0.02				-0.03*** (0.01)		-0.01
Food and accommodation sector	0.01 (0.01)		0.00				0.78 (0.67)		0.02
Gross margin/Sales	-0.96** (0.4)		-0.02				-0.99 (0.63)		-0.19
$\hat{\rho}_3$	-0.78 (0.59)		-0.12						
Business training (indirect effect)	-2.14** (1.03)								
Education (indirect effect)									
Intercept	1.26** (0.64)			-0.89*** (0.28)					
Business cycles		Yes					0.35 (0.33)		
-2 Log Likelihood		1536.9					0.08 (0.27)		
Observations		662					0.10 (0.69)		Yes

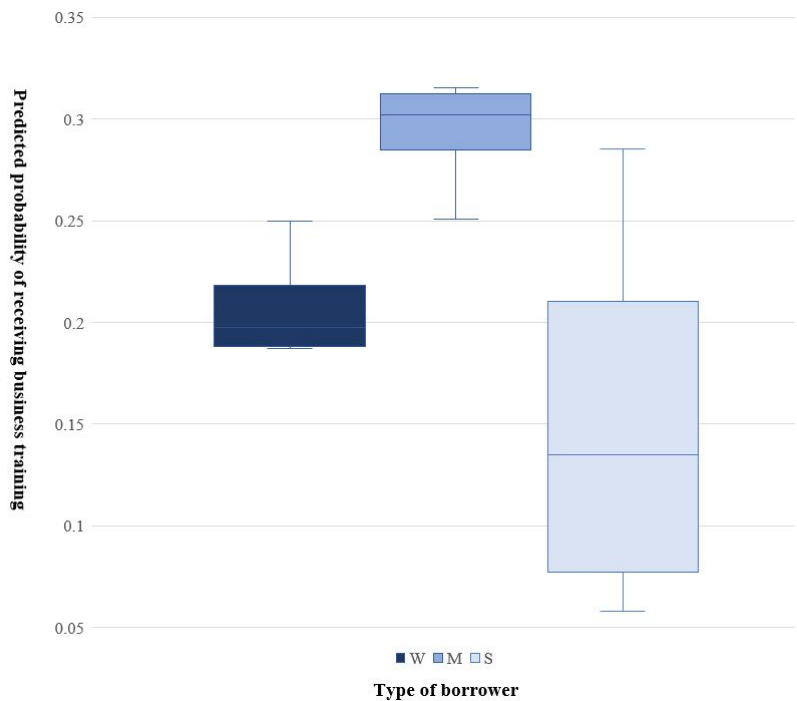
Notes: This table shows the trivariate probit estimation results. Columns (1)–(3) show the results of the estimation of the loan approval equation (4). Columns (4)–(6) show the results of the estimation of the business training equation (3). Columns (7)–(9) show the results of the estimation of the loan default equation (1). Columns (1), (4), and (7) show the estimated coefficients, while average marginal effects are reported in columns (3), (6), and (9). Standard errors are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Figure 2: Predicted probability of receiving business training as a function of predicted borrower risk



Notes: This figure shows the relationship between the predicted borrower risk (horizontal axis) and the predicted probability of receiving business training (vertical axis).

Figure 3: Box plots of the estimated probability to be assigned to business training, by borrower type



Notes: This figure shows the box plots of the predicted probability of receiving a business training according to borrower type (S, M, or W), which is defined by the level of predicted risk. The three groups are formed so as to contain the same number of observations.

5.2. Business training effect and further results

Extant studies are agnostic about the effect of business training on entrepreneurial performance (Garcia and Lensink, 2019). Our paper contributes to this debate by using loan repayment data as a proxy for client performance. In columns (7)–(9) in Table II, we present the estimation results of the loan default equation. According to the

estimates, business training does not significantly impact repayment, corroborating mitigating results on business training efficiency in the microfinance literature (McKenzie and Woodruff, 2014). Yet the non-significance of this relationship may be due to the low variability of the default dummy.

Turning to other control variables, and their marginal effects presented in column (9), we find that male clients are 12% more likely to default than female ones. A similar result is reported by D’Espallier, Guérin, and Mersland (2011) for MFIs in developing countries. Household income and expenses are strong negative and positive determinants of the likelihood of defaulting, respectively. Borrowers who only make a small personal financial contribution to the project and hold few assets are 4% more likely to default. Finally, higher assets are associated with 1% lower credit risk. Concerning heteroscedasticity, the indirect effect of business training is not significant.

The results concerning the loan application review process are presented in columns (1)–(3). As expected, coefficients in the loan approval equation are generally of the opposite sign to those in the risk equation. However, only two variables have a significant impact on loan approval according to Table II. Loan applications by the long-term unemployed and for businesses in the food and accommodation sectors are, respectively, 4% and 2% less likely to be approved by the MFI. However, other variables that significantly impact borrower risk are not significant in the approval equation, suggesting that Créa-Sol has not perfectly optimized its approval process with respect to clients’ credit-worthiness (Roszbach, 2004, reaches similar conclusions using data on consumer loans from a Swedish bank). Finally, $\hat{\rho}_0$ is significant, suggesting that selection bias is real and has to be taken into account.

In terms of instruments’ validity, Appendix 8.4 provides several insights. All instruments used in the business training equation are non-significantly different from zero when included in both the loan approval and default equations (see Table VIII), except in column (8), where *sent by a mainstream bank* is marginally significant at the 10% level.³⁶ The instruments’ validity is confirmed by the standard Heckman selection model for loan repayment controlling for the approval process (see column (1) in Table IX), since all three instrumental variables are non-significant in the loan default equation. Similarly, the standard bivariate approaches using 2SLS and Poisson models suggest that we cannot reject the null hypothesis of valid overidentifying restrictions (see the p-values for the Sargan and Hansen tests in columns (2) and (3) of Table IX).

6. FURTHER ANALYSES AND ROBUSTNESS CHECKS

6.1. *Alternative measure of borrower risk: Duration model*

In the trivariate probit model presented above, we estimated risk through a dummy variable for defaulting loans. Yet as borrowers received microloans at different points in time, some microloans were still active at the time of observation. Moreover, as highlighted by Roszbach (2004), the impact of a default on an MFI’s returns depends to a large extent on when (in the history of the loan) this default occurs. The longitudinal aspect of our data allows us to take into account a strong heterogeneity among defaulting loans. Using this

³⁶Excluding *sent by a mainstream bank* dummy from the set of instruments does not alter our main results. Yet we prefer keeping this instrument in the analysis for the economic reasons presented in Section 4.4.

richer information and considering the fact that some loans were still active at the moment of observation, we provide an alternative measurement of borrower's intrinsic risk to assess the robustness of our results.

We develop this alternative risk metric using a duration model to estimate the survival time of each loan, assuming that survival time follows a Weibull distribution (the most commonly used distribution in applied econometrics, see Lancaster, 1992). The alternative equation used to estimate borrower intrinsic risk and descriptive statistics for loan survival time are outlined in Appendix 8.2. In the business training equation, the predicted *Risk* is measured by the inverse of the expected survival time (rather than by the estimate in Equation (2)). The loan approval equation remains the same as in the trivariate probit model.

The results of this trivariate mixed (probit and duration) model, reported in Table III, are similar to those reported for the trivariate probit model. They confirm the non-monotonic relationship between intrinsic risk and the likelihood of being assigned to a business training course, with effects significant at least at the 5% level (see column (4)).

Column (7) reports the results concerning the effect of business training on the inverse of loan survival time, that is to say, on the instantaneous rate of loan default, called the default hazard rate. Interestingly, in this alternative model, the business training coefficient becomes significant, meaning that business training increases loan survival time (i.e., reduces borrower risk), thereby improving the expected return on the loan for the MFI. This result suggests that business training actually does increase a business's chances of success. The average marginal effect of business training in column (9) suggests that the hazard rate is 33% lower (i.e., the risk is 33% lower) for borrowers receiving business training. Yet the average marginal effects in column (9) are hardly comparable to those reported in the loan default equation in the trivariate probit model, since the risk metric is different. Moreover, as in the trivariate probit model, the indirect effect of business training is non-significant.

Using the results in column (7), we perform a simple back-of-the-envelope cost-benefit analysis by comparing the estimated financial benefits of the training program for the MFI to its total monetary costs, as evaluated by the French General Inspectorate of Finance (see Appendix 8.5). We find that the expected net return of business training – stemming from the increase in survival time – is close to zero, but does not generate any significant loss. This result is in line with existing studies, which are agnostic about the efficiency of business training. However, further research might provide additional insights into the non-monetary benefits of business training (McKernan, 2002).

Taking advantage of the longitudinal information, we find that, in contrast to the trivariate probit model, both the direct and indirect effects of education are significant in the trivariate mixed model. As regards the direct effect, a higher level of education (measured by the number of educational qualifications) significantly decreases a client's riskiness by 26%. Regarding the indirect effect, its significance suggests that a higher level of education increases the variance of the unobserved individual heterogeneity term, v_i . In other words, there is greater uncertainty about the risk of default with more educated borrowers.

TABLE III
TRIVARIATE MIXED MODEL

Dependent variables:	Loan approval			Business training			Inverse of survival time		
	Coef (1)	SE (2)	Average marginal effect (3)	Coef (4)	SE (5)	Average marginal effect (6)	Coef (7)	SE (8)	Average marginal effect (9)
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)		0.23			
Honor loan				0.53*** (0.17)		0.08			
Sent by a mainstream bank				-0.57*** (0.19)		-0.03			
$\hat{\rho}_1$				-0.20 (0.17)					
Business training (direct effect)							-0.41** (0.16)		-0.328
Education (direct effect)							-0.31*** (0.09)		-0.260
Male	-0.01 (0.04)		-0.002				0.59*** (0.14)		0.500
Unemployed at least 12 months	-0.12 (0.11)		-0.03				0.84*** (0.11)		0.511
Single	-0.31*** (0.12)		-0.04				-0.18* (0.11)		-0.095
Household income (in thousand EUR)	-0.001 (0.06)		-0.000				-0.22*** (0.07)		-0.242
Household expenses (in thousand EUR)	0.11* (0.12)		0.04				0.41*** (0.14)		0.240
Low personal investment	-0.22* (0.12)		-0.08				0.83*** (0.10)		0.380
Assets	-0.19* (0.002)		-0.02				-0.01 (0.005)		-0.120
Food and accommodation sector	0.003 (0.17)		0.001				-0.63*** (0.18)		-0.058
Gross margin/Sales	-0.46*** (0.27)		-0.02				-1.39*** (0.23)		-0.635
$\hat{\rho}_0$	-0.45 (0.14)		-0.16						
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)		Yes
Business cycles		Yes							
-2 Log Likelihood		2485.1							
Observations		662							

Notes: This table shows the trivariate mixed estimation results. Columns (1)–(3) show the results of the estimation of the loan approval equation (4). Columns (4)–(6) show the results of the estimation of the business training equation (3). Columns (7)–(9) show the results of the estimation of the inverse of the expected survival time presented in Equation (8) in Appendix 8.2. Columns (1), (4), and (7) show the estimated coefficients, while average marginal effects are reported in columns (3), (6), and (9). Standard errors are in parentheses. ***, **, and * denote significance levels at 1 %, 5 %, and 10 %, respectively.

In addition, our findings in column (7) show that being single, working in the food and accommodation sector, and the gross margin on sales negatively impact borrower risk, whereas these variables were non-significant in the probit model. Further, the Weibull parameter is significant and positive, suggesting that risk increases with time.

Overall, our findings in the trivariate mixed model confirm the importance of the informational content of longitudinal data in the evaluation of business training impact. Ignoring behavioral effects and the longitudinal aspect of defaulting loans might bias results on training efficiency, which may at least partly explain the mixed results in terms of business training impact reported in the existing literature.

When it comes to the loan approval equation, as in the trivariate probit model, loan applications by the long-term unemployed and for businesses in the food and accommodation sectors are, respectively, 4% and 2% less likely to be approved by the MFI. Three other variables appear significant in the trivariate mixed model. A higher household income increases the probability of loan approval by 4%, whereas higher household expenses and a small personal financial contribution to the project decrease it by 8% and 2%, respectively.

6.2. *Intertwining selection and business training provision*

In practice, the examined MFI intertwines its loan application decision with its business training decision, as shown in the decision-making process of the second stage in Figure 1. To account for the fact that loan officers and the MFI internalize the decision about business training assignment during the loan application review process, we develop an alternative nested logit model in Appendix 8.3. This model allows us to relax the assumption that loan approval is strictly sequential and precedes the business training offer by allowing these two processes to be concomitant. In this alternative model, the MFI has three options: rejecting the loan application, approving it without any training, or approving it with training.

The results of the nested logit model are reported in Table IV and are similar to those reported for the previous models. Column (4) displays a non-monotonic relationship between intrinsic risk and the likelihood of being assigned to business training, with effects significant at the 1% level. We conclude that H1 is verified in all our models and that the non-monotonic relationship between business training and borrower risk is indeed robust.

TABLE IV
NESTED LOGIT MODEL

Dependent variables:	Loan approval			Business training			Loan default		
	Coef (1)	SE (2)	Average marginal effect (3)	Coef (4)	SE (5)	Average marginal effect (6)	Coef (7)	SE (8)	Average marginal effect (9)
Explanatory variables:									
Risk (λ_1)				8.14*** (1.13)					
Risk ² (λ_2)				-20.67*** (2.28)					
Other applications				19.22*** (7.26)		0.24			
Honor loan				5.98** (2.58)		0.04			
Sent by a mainstream bank				-7.62** (3.26)		-0.03			
$\hat{\rho}_1$				0.07 (0.04)					
Business training (direct effect)							-0.08 (0.14)		0.06
Education (direct effect)	-0.02 (0.07)		-0.002				-0.07*** (0.01)		-0.04
Male	-0.24 (0.20)		-0.02				0.41*** (0.03)		0.06
Unemployed at least 12 months	-0.65*** (0.21)		-0.03				0.10*** (0.03)		0.01
Single	-0.02 (0.22)		0.001				0.28*** (0.03)		0.04
Household income (in thousand EUR)	0.16 (0.11)		0.02				-0.27*** (0.02)		-0.07
Household expenses (in thousand EUR)	-0.37 (0.23)		-0.05				0.88*** (0.04)		0.22
Low personal investment	-0.33 (0.22)		-0.01				0.28*** (0.04)		0.02
Assets	0.004 (0.004)		0.001				-0.004*** (0.001)		-0.001
Food and accommodation sector	-0.75** (0.31)		-0.01				-0.34*** (0.08)		-0.01
Gross margin/Sales	-0.69 (0.51)		-0.09				-0.56*** (0.09)		-0.14
$\hat{\rho}_0$	-0.91*** (0.13)								
Nested logit parameter (ϕ)	0.03** (0.01)								
Business training (indirect effect)									
Education (indirect effect)									
Intercept	-0.87* (0.52)			-0.57*** (0.13)					
Business cycles		Yes							
-2 Log Likelihood		1531.7							
Observations		662							Yes

Notes: This table shows the nested logit estimation results presented in Appendix 8.3 allowing loan approval and business training decisions to intertwine. Columns (1)–(3) show the results of the estimation of the loan approval equation. Columns (4)–(6) show the results of the estimation of the business training equation. Columns (7)–(9) show the results of the estimation of the loan default equation. Columns (1), (4), and (7) show the estimated coefficients, while average marginal effects are reported in columns (3), (6), and (9). Standard errors are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Akin to the trivariate probit model, business training does not significantly impact loan default according to column (7). Comparing average marginal effects in the loan default equation (between the nested logit and the trivariate probit models) provides additional insights. Although the signs of the effects are the same in both models, more variables appear significant in the nested logit model, and their overall effects are weaker in absolute value. Therefore, accounting for the fact that the MFI intertwines loan approval and business training decisions provides a more nuanced picture, where all control variables have a significant effect but these effects are weaker in absolute terms.

6.3. Including interaction terms with business training

The non-significant effect of business training in the defaulting equation might be driven by the heterogeneity of its impact across different groups of borrowers. Indeed, extant studies support the fact that business training might be more beneficial for some groups of recipients.³⁷ We therefore present the estimates of the trivariate probit model that includes interaction terms between business training and individual characteristics (*education*, *male*, and *unemployed at least 12 months*) in the loan default equation (Table V).

In line with our baseline results in Table II, the coefficients of all the interaction terms are non-significantly different from zero. We conclude that the heterogeneity of the business training impact is not driving the non-significant effect of business training on the probability of default in our baseline model.

6.4. Controlling for loan officer fixed effects

Microfinance loan officers are not only expected to sell loans to potential borrowers but also to assess their repayment capacity, adjust the sizes of the requested amounts, select the applicants as part of lending committees (Battilana and Dorado, 2010), and decide on the assignment to business training, as in the case at Créa-Sol (see Figure 1). Given their multiple roles, loan application review, assignment to business training, and loan repayment are likely to be correlated with loan officers' individual characteristics.³⁸

In this section, we address this issue by controlling for loan officers fixed effects in the three equations of our baseline trivariate probit model. At the moment of data collection, there were four main loan officers working for Créa-Sol. The results are reported in Table VI. Our main results remain robust to the introduction of loan officers' fixed effects, although in line with existing studies, we do observe heterogeneity in loan officer behavior. In particular, the pool of microloans handled by Loan Officer 1 appears to be less likely to default.

³⁷For instance, De Mel, McKenzie, and Woodruff (2014) found training to be more effective for new businesses; Berge, Bjorvatn, and Tungodden (2015) and Giné and Mansuri (2014) discovered that business training had a stronger effect on men; and Biosca, Lenton, and Mosley (2014b) argued that training reduced the probability of living below the poverty line, but only for entrepreneurs who started in a relatively better-off situation.

³⁸Beisland, D'Espallier, and Mersland (2019) found that more experienced loan officers are less likely to serve vulnerable clients, while Beck, Behr, and Guettler (2013) and Blanco-Oliver, Reguera-Alvarado, and Veronesi (2021) indicated that female loan officers served borrowers with lower default rates.

TABLE V
TRIVARIATE PROBIT MODEL WITH INTERACTION TERMS FOR BUSINESS TRAINING

Dependent variables:	Loan approval		Business training		Loan default	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coef	SE	Coef	SE	Coef	SE
Explanatory variables:						
Risk ($\hat{\lambda}_1$)			4.72**	(2.00)		
Risk ² ($\hat{\lambda}_2$)			-6.77**	(3.26)		
Other applications			1.14***	(0.19)		
Honor loan			0.60***	(0.18)		
Sent by a mainstream bank			-0.59***	(0.20)		
$\hat{\rho}_1$			-0.03	(0.27)		
Business training (direct effect)					-0.09	(0.70)
Business training (direct effect)*Education					-0.07	(0.23)
Business training (direct effect)*Male					-0.31	(0.61)
Business training (direct effect)*					0.74	(0.60)
Unemployed at least 12 months						
Education (direct effect)	-0.01	(0.04)			-0.28*	(0.15)
Male	-0.12	(0.11)			1.36***	(0.42)
Unemployed at least 12 months	-0.32***	(0.12)			0.31	(0.33)
Single	0.00	(0.11)			0.48	(0.42)
Household income (in thousand EUR)	0.11*	(0.06)			-0.58*	(0.31)
Household expenses (in thousand EUR)	-0.22*	(0.13)			1.62***	(0.44)
Low personal investment	-0.21*	(0.12)			0.95***	(0.32)
Assets	0.00	(0.002)			-0.06***	(0.02)
Food and accommodation sector	-0.46***	(0.17)			1.32**	(0.53)
Gross margin/Sales	-0.40	(0.28)			-1.87***	(0.44)
$\hat{\rho}_0$	-0.36**	(0.16)				
Business training (indirect effect)					-0.22	(1.16)
Business training (indirect effect)*Education					-0.74	(0.56)
Business training (indirect effect)*Male					2.22*	(1.31)
Business training (indirect effect)*					-0.22	(1.16)
Unemployed at least 12 months						
Education (indirect effect)					0.28	(0.24)
Intercept	0.60**	(0.29)	-0.88***	(0.22)	-0.29	(0.67)
Business cycles		Yes				Yes
-2 Log Likelihood		1524.7				
Observations		662				

Notes: This table shows the trivariate probit estimation results including interaction terms between the business training dummy and *education*, *male*, and *unemployed at least 12 months* variables in the loan default equation. Columns (1) and (2) show the results of the estimation of the loan approval equation (4). Columns (3) and (4) show the results of the estimation of the business training equation (3). Columns (5) and (6) show the results of the estimation of the loan default equation (1). Standard errors are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

TABLE VI
TRIVARIATE PROBIT MODEL WITH LOAN OFFICERS' FIXED EFFECTS

Dependent variables:	Loan approval		Business training		Loan default	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coef	SE	Coef	SE	Coef	SE
Explanatory variables:						
Risk ($\hat{\lambda}_1$)			5.95***	(1.92)		
Risk ² ($\hat{\lambda}_2$)			-9.23***	(3.36)		
Other applications			1.18***	(0.20)		
Honor loan			0.70***	(0.19)		
Sent by a mainstream bank			-0.59***	(0.21)		
$\hat{\rho}_1$			-0.01	(0.07)		
Business training (direct effect)					0.24	(0.35)
Education (direct effect)	-0.05	(0.11)			-0.07	(0.12)
Male	-0.31	(0.29)			0.97***	(0.27)
Unemployed at least 12 months	-0.88*	(0.48)			0.48**	(0.23)
Single	0.02	(0.31)			0.09	(0.25)
Household income (in thousand EUR)	0.27	(0.2)			-0.62***	(0.19)
Household expenses (in thousand EUR)	-0.49	(0.36)			1.21***	(0.31)
Low personal investment	-0.56	(0.39)			0.56**	(0.25)
Assets	0.01	(0.01)			-0.04***	(0.01)
Food and accommodation sector	-1.24	(0.77)			1.32***	(0.44)
Gross margin/Sales	-1.04	(0.90)			-0.80	(0.57)
$\hat{\rho}_0$	-2.66*	(1.49)				
Business training (indirect effect)					0.18	(0.41)
Education (indirect effect)					0.19	(0.12)
Loan Officer 1	0.32	(0.42)	0.16	(0.23)	-0.55**	(0.28)
Loan Officer 2	-0.01	(0.46)	0.51	(0.35)	0.44	(0.32)
Loan Officer 3	0.30	(0.49)	0.23	(0.29)	-0.71	(0.48)
Intercept	0.60**	(0.29)	-0.88***	(0.22)	0.36	(0.68)
Business cycles		Yes				Yes
-2 Log Likelihood		1522.8				
Observations		662				

Notes: This table shows the trivariate probit estimation results including loan officers' fixed effects. Columns (1) and (2) show the results of the estimation of the loan approval equation (4). Columns (3) and (4) show the results of the estimation of the business training equation (3). Columns (5) and (6) show the results of the estimation of the loan default equation (1). Standard errors are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

7. CONCLUSION

This paper is the first to study business training provision associated with financial services in the microfinance context, where lenders are generally better informed about project risk than borrowers who start a business for the first time. In such a setting, loan agreements offered by MFIs may trigger behavioral responses by clients that should be taken into account by lenders offering both financial and non-financial services. First, we show that in theory informed lending can lead to a non-monotonic relationship between borrowers' intrinsic risk and business training provision. MFIs can then use their informational advantages to encourage micro-entrepreneurs to increase the amounts of effort that they expend. This enables MFIs to extend their outreach to riskier borrowers, which is the main objective of MFIs striving to improve financial inclusion. Second, our empirical analysis confirms the non-monotonic relationship depicted in the theoretical model. More particularly, we show that the probability of being assigned to a business training course first increases with a borrower's intrinsic risk and then, beyond a certain threshold, decreases. This relationship is robust to different risk metrics (probability of default or the inverse of loan survival time) and to the alternative nested logit model. Finally, controlling for assignment to business training, we show that business training is efficient since it increases the survival time of loans. Still, our back-of-the-envelope cost-benefit analysis, which compares the total monetary costs of the training program to its financial benefits for the MFI, shows that the expected net return of business training is close to zero. These

findings are new in the literature, which has not studied the impact of business training on loan survival time so far.

Our findings have important policy implications. First, in countries with functional social welfare systems, unemployment benefits can discourage entrepreneurial initiatives (Schreiner and Woller, 2003), more particularly among young people (Doris, O'Neill, and Sweetman, 2020). Provision of subsidized business training (Bourlès and Cozarenco, 2014) to young entrepreneurs (Crépon, Duflo, Huillery, Parienté, and Seban, 2014) is a relevant alternative commonly used in European countries.³⁹ Yet for young trainees, behavioral responses might be exacerbated owing to lack of experience. Hence governments and public agencies should take these responses into account in the design of training programs to curb discouragement and dropping out.

When it comes to external validity, our data was provided by an MFI operating in a developed country where the microfinance sector is still young (Cozarenco and Szafarz, 2020) and the provision of non-financial services is highly subsidized (Bourlès and Cozarenco, 2014). In addition, our sample covers the period between 2008 and 2011, which also overlaps with the financial crisis. While the microfinance industry was, for a long time, considered to be a sector resilient to financial turmoils, several recent studies have pointed out its vulnerability during the 2007-2008 crisis period (Brière and Szafarz, 2015; Wagner and Winkler, 2013). Therefore the extent to which our findings are applicable to microfinance institutions worldwide and during periods unaffected by economic turmoils, needs further probing.

One of the weaknesses of our data set is due to the lack of access to the prior assessment of borrower risk by the MFI. We therefore had to estimate it using a probit or a survival time model. Access to such information would ease the identification and interpretation of our results. Although we undertook several methodological steps towards mitigating endogeneity issues, establishing causality in the relationship between borrower risk and business training provision remains challenging using the data at hand. Hence we caution the reader against drawing strong inferences regarding causal relationships between different processes. Yet strong correlation patterns across baseline and alternative econometric models show that exploring these relationships further would indeed be relevant for policy makers and microfinance sector stakeholders.

Our work opens the way to a further exploration of how informed lending might shape microcredit markets. Beyond patterns of assignment to business training courses, one fruitful avenue for future research would consist in analyzing other strategic ways in which MFIs could use their informational advantage to mitigate the moral hazard problems plaguing the microcredit market in the absence of collateral. For example, it might be interesting to examine how informed lending might modify the dynamics of microloan agreements in settings where borrowers can apply for a microloan several times within the same MFI (progressive lending) or from several MFIs (competitive markets).

More generally, our paper and the existing literature studying the behavioral implications of training provision have been silent about their longer-term impacts and spillover on the trainees' professional and personal networks (Kugler, Kugler, Saavedra, and Herrera-Prada, 2022). Addressing these issues in the microfinance market, as well as the labor market, education, and family contexts could be of particular interest for policymak-

³⁹See European Microfinance Network publications on Legislative Mapping Reports for European countries.

ers.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the authors. The data are not publicly available owing to privacy or ethical restrictions.

8. APPENDIX

8.1. An illustration of our discrete theoretical mechanisms

Consider a borrower who needs to finance a project, of size normalized to 1. He/she has no collateral and is unable to make a personal financial contribution to the project. He/she thus needs to borrow the totality of the funds from the MFI. If launched, the project generates a return, ρ , in the case of success and 0 in the case of failure. 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 project success is denoted $p(\theta, h, e)$. It depends on borrower type θ , borrower effort e , and the level of business training from the MFI h . We assume that the probability of success will increase in conjunction with these three parameters. The parameter θ represents the intrinsic probability of success (or type) of the borrower, depending on borrower and project characteristics, and excluding the effects of business training and effort: $p(\theta, 0, 0) = \theta$. We assume that the efficiency of business training decreases with type: $\frac{\partial^2 p}{\partial \theta \partial h} \leq 0$. Effort is costly for the borrower and business training is costly for the MFI. These costs are denoted by $\psi(\theta, e)$ and $\varphi(h)$, respectively.⁴⁰ We assume that the (psychological) cost of effort is type-dependent and decreases with type: $\psi(\theta, 0) = 0$ and $\frac{\partial \psi}{\partial \theta} \leq 0$. Once a borrower has been issued a loan, the MFI maximizes profit (or minimizes loss) on this borrower and is assumed to be risk neutral. Then, once the project has been accepted, its objective function is given by: $p(\theta, h, e)R - \varphi(h)$. Similarly, the utility of a risk-neutral borrower is given by: $p(\theta, h, e)(\rho - R) - \psi(\theta, e)$.⁴¹

In the simple discrete version of the model, we assume 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: $\theta \in \{W, M, S\}$.⁴² We assume $\varphi(0) = 0$, $\varphi(1) = \phi$ and denote the efficiencies of training and effort by $\Delta_h p(\theta, e) \equiv p(\theta, 1, e) - p(\theta, 0, e)$ and $\Delta_e p(\theta, h) \equiv p(\theta, h, 1) - p(\theta, h, 0)$. According to previous assumptions, $\Delta_h p(\theta, e)$ decreases with θ . To highlight the role of informed lending, we focus on intuitive cases in which the relationship between training and borrower type is monotonic under perfect information, through the following assumptions:

ASSUMPTION 1 (i) $\forall e$, $\Delta_h p(W, e) \geq \Delta_h p(M, e) \geq \frac{\phi}{R} \geq \Delta_h p(S, e)$ and (ii) $\forall h$, $\frac{\psi(M, 1)}{\rho - R} \geq \Delta_e p(M, h) \geq \Delta_e p(S, h) \geq \frac{\psi(S, 1)}{\rho - R}$ and $\frac{\psi(W, 1)}{\rho - R} \geq \Delta_e p(W, h)$

⁴⁰Our results hold when training is costly for borrowers, as long as this cost is type-independent and their participation constraints are satisfied when they receive training.

⁴¹Our results directly extend to the case of risk-averse borrowers with utility function $u(\cdot)$, provided ψ is defined in terms of utility and $u(0) = 0$. The expected utility then writes: $p(\theta, h, e)u(\rho - R) - \psi(\theta, e)$.

⁴²Most of the mechanisms hold in a model with a continuum of types and a continuum of effort, but formal conditions are less intuitive.

Under perfect symmetric information, Assumption 1 leads the MFI to provide business training to the two weakest types: W and M (if approved), and not to provide any business training to the strongest type: S. Borrowers of type S make an effort but the two weakest types do not. Then, under perfect information, weak-type borrowers are pooled with medium-type borrowers.

Let us now analyze the various cases that may occur with an informed lender, depending on the type of borrowers that get approved. Consider first that all three types of projects are approved. The next proposition shows that in the unique non-pooling Perfect Bayesian Equilibrium (PBE), the MFI only trains M-type borrowers.⁴³ In this case, borrowers noting that they are not being assigned to a training course infer that they are either weak (W) or strong (S) types. Let us denote by α the probability that a borrower is actually an S type ($(1 - \alpha)$ is then the probability that he/she is actually a W type). At equilibrium, α equals borrowers' beliefs that they are a strong type once they have realized that the MFI has decided not to train them. Similarly, borrowers noting that the MFI has decided to train them are convinced that their type is M.

PROPOSITION 1 *When all projects are approved under informed lending, the unique (semi) separating PBE is such that (i) the MFI provides business training only to M-type borrowers, and (ii) only S-type and W-type borrowers exert effort, provided that:*

$$(5) \quad \Delta_{hp}(W, 0) - \Delta_{ep}(W, 0) \leq \frac{\phi}{R} \leq \Delta_{hp}(M, 0) - \Delta_{ep}(M, 0)$$

$$(6) \quad \alpha \Delta_{ep}(S, 0) + (1 - \alpha) \Delta_{ep}(W, 0) \geq \alpha \frac{\psi(S, 1)}{(\rho - R)} + (1 - \alpha) \frac{\psi(W, 1)}{(\rho - R)}$$

The first condition guarantees that the MFI has an incentive to train M-type borrowers, although they subsequently will not make any effort, but not W-type borrowers, although they will make an effort. The second condition guarantees that W-type borrowers indeed will make an effort if they are not trained. If the share of S-type borrowers is high enough, borrowers believing that they are either S or W type have an incentive to make an effort. Together with the assumption that the efficiency of training (i.e. $\Delta_{hp}(\theta, e)$) decreases with borrower type θ , condition (5) implies that the efficiency of effort is higher for W-type than for M-type, when they receive no training: $\Delta_{ep}(W, 0) > \Delta_{ep}(M, 0)$. As, under assumption 1, M-type has an incentive to provide effort, contrary to W-type, this translates into a higher cost of effort for W-type (than for M-type): $\psi(W, 1) > \psi(M, 1)$.

We denote this equilibrium E^* . Under condition (6) the perfect information outcome is not a PBE. Indeed, such an equilibrium would imply that the 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.

E^* is the only semi-separating PBE (in pure strategies) when projects of all types are approved. Under (5) we have $p(M, 1, 1)R - \phi \geq p(M, 1, 0)R - \phi \geq p(M, 0, 1)R \geq$

⁴³ A pooling equilibrium in which all borrowers are assigned to business training courses and all make an effort can also exist. However, as always is the case with a pooling PBE, it requires stringent conditions governing beliefs outside the equilibrium (that is when borrowers are not trained). We therefore rule out this equilibrium and focus on the semi-separating one described in this subsection.

$p(M, 0, 0)R$, and the MFI 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 $p(W, 1, e)R - \phi \geq p(W, 0, 0)R$).

Now let us assume that W-type projects are rejected. Under Condition (5), when only M and S types are approved, the only equilibrium is the perfect information one (since the MFI has an incentive to train M-type borrowers, no pooling equilibrium can exist). Thus, if only M and S-type projects are approved, then at the second stage the MFI will only provide training to M-type borrowers and S-types will exert effort, whereas M-types will not. Finally, if only S-type projects are approved, then the MFI will not provide any training and all agents will exert effort. In the following, we formalize the loan approval stage and discuss the overall objective of the MFI. At the selection stage, when deciding whether to approve a loan, the MFI takes into account a potential subsequent assignment to a business training course. We then show that informational advantage of lenders can lead to higher approval rates of W-type borrowers. This holds both for MFIs seeking to maximize their profits (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 2 *Under the conditions listed in Proposition 1, the MFI earns a greater expected profit under informed lending than under symmetric information. Informed lending increases outreach:*

- of a non-profit MFI if lending to the riskiest borrowers (W-type) is not profitable under symmetric information, i.e., if $p(W, 0, 1)R < 1 + \phi$
- of a for-profit MFI if lending to the riskiest borrowers (W-type) becomes profitable under asymmetric information, i.e., if $1 \leq p(W, 0, 1)R < 1 + \phi$.

As shown above, the only difference between the symmetric and asymmetric information cases concerns W-type borrowers if their loans are approved by the MFI. Under symmetric information, they do not exert any effort but do receive business training; whereas under informed lending, they do not receive any business training but do exert effort. Thus, under condition (5), the MFI makes a greater profit on W-type projects (and thus a greater overall profit) when it has information advantage. MFIs engaging in cross-subsidization (i.e., non-profit MFIs)⁴⁴ can then finance more W-type projects under informed lending in situations where they would have had a negative expected profit for W-type projects under symmetric information. This also applies to for-profit MFIs, provided they also make positive expected profits for W-type borrowers under informed lending.

8.2. Inferring risk using loan survival data

This section extends borrower risk metric from the probit equation to a duration equation by adding information on the survival time of a loan, T_i . The alternative metric of risk

⁴⁴Cross-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).

consists 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 and accounts for the fact that some loans are still active at the moment of observation. Indeed our data on loan applications covers the period from May 2008 to May 2011, for stages 1 and 2 in Figure 1. Yet data on repayment performance (stage 3) has been collected in October 2011. 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 when 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 $y_{1i} = 1$, i.e., $T_i = t_i$, or it is censored because the loan is still active when $y_{1i} = 0$, i.e., $T_i > t_i$.

Table VII presents descriptive statistics on the survival time of each microcredit.

TABLE VII
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

Notes: This table shows the descriptive statistics on the survival time of defaulting and performing loans.

We estimate survival time for each loan using a duration model assuming that survival time follows a Weibull distribution, which is commonly used in applied econometrics (Lancaster, 1992).

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

where $\mu_i \equiv \exp(w_i'\beta_1 + \eta\mathbf{B}_i + \alpha_1y_{2i} + \rho_{1i}v_i)$ and $\rho_{1i} \equiv \exp(\alpha_2y_{2i} + \delta Education_i)$.

The expected survival time is given by:

(8) $\mathbb{E}(T_i|w_i, \mathbf{B}_i, y_{2i}, v_i) = \mu_i^{-1}\Gamma\left(1 + \frac{1}{\sigma}\right)$

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 risk is necessarily inversely related to expected survival time. We consider an alternative measure of risk given by the inverse of $\mathbb{E}(T_i|w_i, v_i)$ and replace $Risk = \Phi(w_i'\beta_1 + v_i)$ by $Risk = [\mathbb{E}(T_i|w_i, v_i)]^{-1}$ in the business training decision-making process.

8.3. Nested logit

In this model we allow for the loan application review and the business training provision 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 trivariate probit model and denote by $\Lambda(\cdot)$ the logistic cumulative distribution function: $\Lambda(x) \equiv [1 + \exp(-x)]^{-1}$):

$$\begin{aligned} \mathbb{P}(y_i = 0) &= \mathbb{P}(y_{0i} = 0) = 1 - \mathbb{P}(y_{0i} = 1) = \Lambda(-(w_i'\beta_0 + \eta_0\mathbf{B}_{0i} + \phi IV_i + \rho_0\nu_i)) \\ \mathbb{P}(y_i = 10) &= \mathbb{P}(y_{0i} = 1, y_{1i} = 0) = \mathbb{P}(y_{0i} = 1)\mathbb{P}(y_{1i} = 0|y_{0i} = 1) \\ &= \mathbb{P}(y_{0i} = 1) [1 - \Pr(y_{1i} = 1|y_{0i} = 1)] \\ &= \Lambda(w_i'\beta_0 + \eta_0\mathbf{B}_{0i} + \phi IV_i + \rho_0\nu_i)\Lambda\left(-\phi^{-1}(x_i'\beta_2 + \lambda_1 Risk + \lambda_2 Risk^2 + \rho_2\nu_i)\right) \\ \mathbb{P}(y_i = 11) &= \mathbb{P}(y_{0i} = 1, y_{1i} = 1) = \mathbb{P}(y_{0i} = 1)\mathbb{P}(y_{1i} = 1|y_{0i} = 1) \\ &= \Lambda(w_i'\beta_0 + \eta_0\mathbf{B}_{0i} + \phi IV_i + \rho_0\nu_i)\Lambda\left(\phi^{-1}(x_i'\beta_2 + \lambda_1 Risk + \lambda_2 Risk^2 + \rho_2\nu_i)\right) \end{aligned}$$

where $IV_i \equiv \ln [1 + \exp (\Lambda (\phi^{-1}(x_i'\beta_2 + \lambda_1 Risk + \lambda_2 Risk^2 + \rho_2\nu_i)))]$ 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 $Risk = \Phi(w_i'\beta_1 + \nu_i)$.

8.4. Validity of instruments

In this section, we provide additional information on the validity of our identification methods. First, following Delis, Hasan, Iosifidi, and Ongena (2022), we provide evidence that our instrumental variables used in the business training equation do not directly explain the defaulting and approval dummies. Next, using classical bivariate approaches based on 2SLS and Poisson models, we show that we cannot reject the null hypothesis of valid overidentifying restrictions.

TABLE VIII
DIRECTLY CONTROLLING FOR OTHER APPLICATIONS, HONOR LOAN, AND SENT BY A MAINSTREAM BANK

Dependent variable:	Loan approval				Loan default			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explanatory variables:								
Other applications	0.09 (0.11)			0.09 (0.12)	−0.16 (0.19)			−0.12 (0.21)
Honor loan		0.02 (0.10)		−0.01 (0.12)		−0.15 (0.18)		−0.18 (0.21)
Sent by a mainstream bank			0.18 (0.14)	0.18 (0.14)			−0.34 (0.23)	−0.41* (0.24)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business cycles	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	662	662	662	662	337	336	336	336

Notes: This table shows the results of specifications that replicate Equations (1) and (4) estimated separately using a probit model. We include *other applications*, *honor loan*, and *sent by a mainstream bank* (our IVs) directly in the models, separately and then concomitantly, to show that these variables do not significantly correlate with *defaulting* and *approval* dummies. Columns (1)–(4) replicate Equation (4) for loan approval, and Columns (5)–(8) replicate Equation (1) for loan default. Standard errors are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

TABLE IX
INSTRUMENTS' VALIDITY TESTS – BIVARIATE MODELS

Model	Heckman		IV regression		IV duration	
Risk measure	Loan default		Loan default		Inverse of survival time	
Explanatory variables	(1)		(2)		(3)	
Business training	-0.033	(0.050)	0.008	(0.097)	-1.832**	(0.927)
Male	0.117**	(0.046)	0.122***	(0.045)	0.753**	(0.374)
Education	-0.034**	(0.016)	-0.038**	(0.016)	-0.231**	(0.102)
Single	0.037	(0.048)	0.034	(0.048)	-0.188	(0.314)
Unemployed for over 12 months	0.057	(0.054)	0.054	(0.048)	0.463	(0.350)
Household income (in thousand EUR)	-0.061**	(0.026)	-0.053**	(0.024)	0.004	(0.187)
Household expenses (in thousand EUR)	0.133**	(0.055)	0.134***	(0.050)	0.533*	(0.293)
Low personal investment	0.090	(0.056)	0.099*	(0.051)	0.193	(0.305)
Assets (in thousand EUR)	-0.002**	(0.001)	-0.002**	(0.001)	-0.025**	(0.013)
Food and accommodation sectors	0.030	(0.082)	0.041	(0.076)	0.774*	(0.444)
Gross margin(EUR)/Sales(EUR)	-0.250**	(0.119)	-0.278**	(0.108)	-1.085*	(0.599)
Other applications	-0.058	(0.054)				
Honor loan	-0.006	(0.049)				
Sent by a mainstream bank	-0.090	(0.055)				
Intercept	0.491***	(0.140)	0.402***	(0.122)	-0.124	(0.746)
Business cycles	Yes		Yes		Yes	
Observations	662		332		332	
Tests of overidentifying restriction:						
Sargan Chi ²			3.988	(0.136)		
Hansen Chi ²			3.794	(0.150)	0.850	(0.654)

Notes: This table shows the results of bivariate models to further explore the validity of our IVs. In column (1) we perform a Heckman estimation using loan approval and default equations. In this model *other applications*, *honor loan*, and *sent by a mainstream bank* are introduced directly in the risk equation to show that these variables do not significantly correlate with the *defaulting* dummy. In columns (2) and (3) we perform instrumental variables models using a 2SLS and Poisson regression models, respectively. They allow us to perform Sargan and Hansen tests of overidentifying restrictions for which we report the Chi2 statistics and the p-value in the parentheses. Standard errors are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

8.5. A cost–benefit analysis of business training

Business training provided on a par with financial services is often subsidized, especially in Western Europe (Pytkowska, 2021). Therefore, it is crucial for the MFI and policymakers to assess whether offering a business training program in the context of microcredit justifies taxpayers’ exposure to this market. Previous research has focused on the cost-benefit analysis of microlending and indirect subsidies, in particular in the form of loan guarantees.⁴⁵ In this section, we follow this approach by comparing the total (monetary) costs of the training program and its financial benefits to the MFI.

The various parts of the analysis are presented in Table X. First, we rely on the information provided by the French General Inspectorate of Finance to estimate the cost of business training for each borrower enrolled at an average cost of EUR 830.⁴⁶ Our purpose is to compare this cost to the average expected benefits derived from training. To this end, we compute the average return of business training, measured by the increase in survival time stemming from assignment to training for a typical microloan (in terms of loan size, duration, and interest rate).

Second, to estimate the average predicted survival time, we use the results of the trivariate mixed model reported in Table III.⁴⁷ Using the coefficients in column (7), we predict:

⁴⁵Bourlès and Cozarenco (2018) find that subsidization of micro-borrowers is an efficient policy since the net losses due to defaults are largely covered by the interest returns and the welfare benefits saved over the loan period.

⁴⁶The French General Inspectorate evaluates the total cost of the NACRE program – which is similar to the one from which the borrowers in our sample benefited – to EUR 830 per beneficiary (Schechter, Toussain, Thomas, Abrossimov, and Colas, 2013).

⁴⁷We rely on the estimate of the trivariate mixed model as it entails more variation in the cost of default

the survival time for borrowers who received business training (n=196), controlling for their individual and business characteristics; and the counterfactual survival time for these borrowers, if they had not received non-financial services (by setting the business training dummy to 0). Each individual prediction is bounded by the average loan duration (52 months). We find that the average survival time is equal to 39.6 months for borrowers who have received business training against 35.2 months for their counterfactual counterparts. The difference between these two averages is equal to 4.4 months. It corresponds to the additional survival time of loans generated thanks to business training.

Next, we use this estimated gain in terms of loan survival time, to compute the expected gross and net returns – with and without business training – for a typical microloan as described in Section 3.1, with an average loan amount of EUR 8,900, an average interest rate of 4.2%, and a mean maturity of 52 months. This allows us to compute the expected gross return, including capital and interest, for borrowers receiving business training and their counterfactual counterparts, which is equal to EUR 7,425 and EUR 6,600, respectively. The difference between the two gross returns is equal to EUR 825, which is almost equal to the average cost of training (EUR 830), suggesting that the financial return of business training to the MFI is close to zero.

Our simple back-of-the-envelope cost-benefit analysis shows that the expected net return of business training (i.e., accounting for the cost of business training) is almost nil. This result is in line with existing studies, which are agnostic about the efficiency of business training (Garcia and Lensink, 2019; McKenzie and Woodruff, 2014). According to our results, subsidizing business training is not profitable in terms of financial returns to the MFI. Yet it does not generate any significant losses. Further research is needed to study the non-monetary benefits of non-financial services to their beneficiaries, which are not taken into account in our analysis, for example through increased social and human capital (McKernan, 2002).

TABLE X
COST-BENEFIT ANALYSIS OF BUSINESS TRAINING

	Borrower with training	Counterfactual borrower without training	Difference
Average cost of training (EUR)	830	0	830
Average predicted survival time (months)	39.6	35.2	4.4
Loan characteristics			
Average loan size (EUR)	8,900	8,900	–
Average interest rate	4.2%	4.2%	–
Average loan duration (months)	52	52	–
Returns			
Expected capital return (EUR)	6,629	5,846	783
Expected interest return (EUR)	796	754	42
Expected gross return (EUR)	7,425	6,600	825
<i>Expected net return</i>	6,595	6,600	–5

Notes: This table shows the results of a simple back-of-the-envelope cost-benefit analysis for borrowers receiving business training and their counterfactual counterparts.

and predicts a significant effect of business training.

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