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The Plus in Credit-Plus-Technical Assistance: Evidence from a Rural Microcredit Programme in Bolivia

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ABSTRACT *Microfinance institutions traditionally focus on the provision of credit and other financial services. In light of recent evidence on the scant transformative effects of 'standard' microcredit models, however, some lenders are increasing efforts to offer additional non-financial services – such as business trainings and technical assistance. While literature on the effects of business trainings is quite voluminous, far less attention has been paid to microcredit in combination with technical assistance, especially salient in rural contexts. This study investigates a programme launched by Sembrar Sartawi, a Bolivian MFI, which complemented dairy farming credit with the provision of agronomic and veterinarian expertise. We collect data of approximately 600 dairy farmers from the Bolivian plateau over two data-collection waves, and conduct a variety of cross-sectional and panel regression analyses. We find that technical assistance has positive, statistically significant, and economically salient impacts on monthly revenues and milk production. Our study strongly suggests that providing access to technical assistance can be a very effective 'plus' instrument for MFIs providing financial services to rural clients. We also point at the importance of conducting further research related to cost-effectiveness, to assess whether MFIs may expand technical assistance and at the same time achieve self-sustainability.*

1. Introduction

Traditionally microfinance institutions (MFIs) focus on the provision of financial services, especially microcredit, to relatively poorer borrowers. It is therefore no surprise that most evaluations of microfinance programmes deal with the impact of microcredit in terms of income increase and poverty alleviation. The majority of these studies suggest that the impact of microcredit is probably much smaller than expected (see e.g. Banerjee, Karlan, & Zinman, 2015). While the overall contribution of microcredit remains ambiguous (see e.g. Dahal & Fiala, 2020), most recent studies tend to agree that its 'standard' model should not be expected to raise a substantial amount of clients out of poverty. This is especially true for microcredit directed to poorer smallholder farmers, where MFIs have struggled to sustainably

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replicate some of the successes obtained with off-farm microentrepreneurs (e.g. Crépon, Devoto, Duflo, & Parienté, 2015; Li, Gan, & Hu, 2011; Tarozzi, Desai, & Johnson, 2015).

In order to improve the poverty-reducing impacts of their programmes, several MFIs have started to provide non-financial services – commonly labelled *credit-plus* – such as business trainings and technical assistance. While the literature on the impact of business trainings is quite voluminous by now (see e.g. Biosca, Lenton, & Mosley, 2014; Bulte, Lensink, & Vu, 2017; Valdivia, 2015),[1] much less attention has been paid to technical assistance in a credit-plus context. To the best of our knowledge, no study has yet rigorously tested the role of technical assistance provided by an MFI. Both technical assistance and business trainings aim to enhance the human capital of the borrower, albeit in a completely different way: where business trainings try to improve managerial processes, technical assistance focuses on the production practices of goods and services. As a result, we should expect very different outcomes as a result of these different non-financial services provided on top of credit provision.

The lack of sufficient human capital has often been recognised as one of the key factors limiting the impact of microcredit (e.g. Banerjee, 2013; Halder & Mosley, 2004). In fact, many micro-entrepreneurs, and especially smallholder farmers in relatively poor contexts, typically lack technical skills to ensure that the most efficient production processes are consistently in place. In this case, simply providing access to financial capital (i.e. access to microcredit) will not enhance production substantially, and hence not reduce poverty. If financial capital and human capital are complements, it is likely that access to financial capital will only increase production if it is accompanied by some form of knowledge transfer aimed at increasing productivity. This will certainly be the case if human capital is the more binding constraint within the production function.[2] In light of this, it is surprising that rigorous evaluations of the additionality effect of technical assistance within credit-plus programmes are not available. This paper is the first that explicitly examines the importance of providing technical assistance to smallholder farmers, in addition to microcredit.

This research investigates a programme launched in 2016 by Sembrar Sartawi, a Bolivian MFI. Specifically, we study an ongoing technical assistance programme which supports borrowers dedicated to milk production in the Province of Aroma (Department of La Paz). By focusing on a homogeneous group of smallholder farmers (milk producers), we avoid power problems as much as possible. We collect data of approximately 600 farmers from the Bolivian plateau over two data waves, and conduct a variety of cross-sectional and panel regression analyses. The study shows that technical assistance provided to Sembrar Sartawi clients has positive, statistically significant and economically salient impacts on farmers' welfare – proxied by monthly sales, and daily milk production. The most conservative intent-to-treat estimates find an 11 per cent increase of daily milk production of and a 16 per cent increase in monthly revenues among those with access to technical assistance. These results are robust to several different cross-sectional and panel estimation methods, as well as over time. Results related to profits are less robust, ranging from zero to over 40 per cent increases depending on the specification and survey wave – as is characteristically the case for variables captured with higher noise and more outliers. Taken together we believe that these results strongly suggest that providing access to technical assistance can be a very effective 'plus' instrument for MFIs providing financial services to smallholder farmers, especially in poor rural contexts characterised by ample margins to increase productivity, when properly assisted. Moreover, our qualitative survey shows that several farmers remained member of the microfinance organisation, because this would give them free access to technical assistance, which further underpins the importance of technical assistance for them and the MFI.

The rest of this study proceeds as follows. In section 2 we discuss existing related work and explain how our paper contributes to the literature. Section 3 describes the microcredit and technical assistance programmes as well as the context of the study area. Section 4 presents the sampling strategy and describes the data. Section 5 introduces the estimation strategy. In Section 6 we present the main results, while Section 7 concludes and outlines areas of further research.

2. The microfinance-plus literature

MFIs provide different types of financial services, such as credit, savings, insurance, transfers and payments. However, to an increasing degree, they also provide non-financial services, specifically social services, business services and technical assistance. The microfinance-plus literature deals with MFIs providing a combination of financial and non-financial services, and focuses specifically on the impact of the non-financial services, together with access to credit.[3]

There are several studies that have evaluated the effects of MFI social services, especially of health education. Well-known examples are De La Cruz et al. (2009), Pronyk et al. (2006, 2008), Karlan, Thuysbaert, and Gray (2017) and Kim et al. (2009). Some of these studies, specifically deal with the impact of health training on maternal and child health and family planning (see e.g. Desai & Tarozzi, 2011; Flax et al., 2014; Hamad, Fernald, & Karlan, 2011; Smith, 2002). In general, these studies suggest that microcredit becomes more effective when provided together with a health training. Moreover, most studies show that health education increases health knowledge, while the impact on health behaviour is mixed.

There are also many studies that have evaluated the impact of business services, especially in the form of business trainings. Recognised examples are Berge, Bjorvatn, and Tungodden (2015), Bulte et al. (2017), De Mel, Mckenzie, and Woodruff (2014), Giné and Mansuri (2014), and Karlan and Valdivia (2011). Most studies find that entrepreneurship trainings improve business knowledge, and, to a lower degree, business practices. However, almost none of these studies find that business outcomes are significantly improved by the entrepreneurship training. One of the few exceptions is Bulte et al. (2017), who focus on a training that specifically focus on female entrepreneurs. They consider the impact of the Gender and Entrepreneurship Together Ahead (GET-Ahead) training, which combines modules on gender and entrepreneurship, provided by a Vietnamese MFI. Bulte et al. (2017) uncover some positive effects on profits and business entry and exit. Huis, Lensink, Vu, and Hansen (2019) provide evidence that the Get-Ahead training has also improved female empowerment of participating members of the Vietnamese MFI. Some related studies specifically deal with financial literacy trainings, see e.g. Bruhn and Zia (2013), Drexler, Fischer, and Schoar (2014) and Sayinzoga, Bulte, and Lensink (2016). In line with most other studies analysing microfinance-plus interventions, these studies find that especially (financial) knowledge has been improved by the training. Impacts on economic outcomes like savings, income and wealth are minor.

While the literature on the impact of both social services and business trainings provided by MFIs is quite voluminous by now, much less attention has been paid to the role of technical assistance. In particular, it is beginning to be argued that technical assistance provided by MFIs may have profound positive effects. In line with business trainings, technical assistance aims to improve human capital. However, while business trainings primarily try to improve business management, technical assistance aims to enhance production methods directly. Consider for instance a MFI providing technical assistance to tomato producers. The technical assistance would include advise on e.g. the choice of seeds, pest control, use of fertilisers and sowing and harvest processes. A business training would deal with accounting and/or financial issues. Technical assistance can be delivered through technical training workshops. A well-known example is the Agriculture Extension Programme by BRAC (2016). With this programme, BRAC offers large-scale demonstrations to teach farmers how to use new agricultural technologies, cultivate new varieties of crops, and improve production practices. Technical assistance can also be customised directly to the microentrepreneur's needs. In this case, the assistance is provided individually by a specialist who has a one-to-one relationship with the client.

To the best of our knowledge there is no quantitative study available that exclusively analyses technical assistance provided by an MFI. Caretta (2014) conducts a qualitative case study, using focus groups, to examine the effects of an agricultural training for female members of Kenyan village savings-and-loan programmes. The study suggests that the training has improved bargaining power of participating women. Valdivia (2015) also considers the impact of technical assistance, but only in combination with several other non-financial services. Our paper contributes to the small literature on technical assistance provided by MFIs. It is the first attempt to examine with a quantitative analysis the additionality effect of technical assistance provided individually by a specialist to farmers, who are members of a MFI.

3. Background and study setting

3.1. Milk production in the Aroma Province, Bolivia

Our study takes place in the Province of Aroma, in the Bolivian Plateau. Relatively close to Bolivia's largest city La Paz, Aroma is one of the areas with relatively high milk production. Since the sixties, the government as well as several international organisations have explicitly promoted milk production in order to improve the economic situation of smallholder dairy producers in the plateau and enhance milk consumption all over the country. The support to improve milk production has mainly been extended by providing grants (e.g. to improve farm infrastructure). Not much attention has been given over the years to improving production practices of smallholder dairy farmers, for instance in the form of technical assistance. As a result, still nowadays many farmers lack proper practices to guarantee consistently high quantity and quality of milk (e.g. preventing mastitis and other diseases, maintaining low constant temperatures, improving alimentation to ensure high fat content). Their production is typically low, irregular, and frequently rejected by processors and aggregators.

Milk production in the Aroma Province is concentrated in four municipalities: Ayo, Patacamaya, Sica Sica and Umala. Sembrar Sartawi is accessible to borrowers in all four of these municipalities, as are several other banks and microfinance institutions. Milk producers typically sell milk to the two largest milk companies (Pil and Delizia); they also produce cheese. In 2016, about a year before we conducted the baseline survey, farmers in the area suffered from several shocks: there was a severe drought which affected the forage and water available to feed their cattle, the average price of the milk decreased from 3.5 Bolivianos[4] to 3 Bolivianos, and one of the milk companies introduced a quota that reduced and limited the litres of milk that farmers delivered every day to the company. These shocks induced many farmers to reduce their cattle, and hence their milk production. Some engaged in new production activities or migrated to urban areas.

3.2. The microcredit and technical assistance programmes

Sembrar Sartawi focuses on disbursing loans in the form of microcredits to help farmers in rural areas perform and expand their productive activities. In addition, it offers technical assistance as a service complementary to the microcredit programme. The technical assistance programme is unique in Bolivia, as Sembrar Sartawi is the only MFI in Bolivia that provides technical assistance as a customised service to its clients. By providing technical assistance, Sembrar Sartawi obtains a competitive advantage over other financial intermediaries in the region.

At the time of the study, Sembrar Sartawi had 4 office branches and 40 agencies all over Bolivia. Our study deals with the agency in the Aroma province, as especially in Aroma province milk producers are served. Sembrar Sartawi uses strict eligibility rules. In order to become a client, a farmer must fulfil three requirements: 1) live in the community for at least 2 years; 2) be engaged in milk production, and 3) be between 18 and 65 years old. If a farmer meets these criteria, they can receive different types of loans, which are repaid on a monthly basis. Sembrar Sartawi offers loans to milk producers, selling milk to the two largest milk buying companies in Bolivia. For this loan type, a farmer signs a contract with one of the two milk buying companies and commits to deliver their milk every day. These loans are considered low-risk loans since borrowers receive bi-weekly payments and Sembrar Sartawi collects repayments directly from the milk companies. Due to the low risk character, the interest on these loans is relatively low (16–18%) and collateral is not required. Sembrar Sartawi also offers loans to farmers who produce cheese or sell milk to other buyers. These borrowers receive loans at an average annual interest rate of 26.5 per cent and do require collateral.

In addition to microcredit, Sembrar Sartawi offers technical assistance to their clients, to help them improve their production of milk and enhance their productivity-increasing practices. Access to technical assistance is optional and exclusive to clients. This service is provided by a technician with a veterinary degree, who is a full-time employee of Sembrar Sartawi. While the service is in principal without additional charge/costs, costs for medicines (or suggested improved inputs) need to be covered. The technician delivers general and customised assistance to the clients. The technician provides technical assistance to many farmers at the same time by means of technical training workshops, and also organises monthly workshops in the communities and yearly visits to farms and experimental centres based on clients' needs and interests. In addition to the workshops, the technician provides personalised assistance, helping only one client at a time: he or she serves clients through individual visits to their farms and tries to deal with their specific requests. The technical assistance programme consists of five elements: (a) cattle sanitation to prevent and treat diseases, (b) cattle nutrition to prepare and optimise feed and efficiently use resources such as the native prairies, (c) cattle reproduction to enhance genetics, treat reproductive diseases and assist during pregnancy and births, (d) cattle management to improve caring practices, such as quarantine in the purchase of cattle, cattle deworming, barn cleaning and calf special care, and (e) milk transformation to improve milking practices and teach alternative transformation processes for more efficient use of milk. The Sembrar Sartawi technical assistance programme in Aroma Province started in August 2016.

4. Sampling and data

4.1. Sampling strategy

Our study population is composed of milk producers from the Province of Aroma. Everybody has access to microcredit, either from the MFI we set to investigate, or from another financial intermediary.[5] However, only members of Sembrar Sartawi have access to technical assistance.

We conducted a baseline survey in October 2017, about a year after the start of the technical assistance programme. The survey has been organised in collaboration with a local research institute, INESAD. We visited 39 communities, in four municipalities, Ayo, Patacamaya, Sica Sica, and Umala. In these communities, we targeted the entirety of clients of Sembrar Sartawi. However, as a few clients were unavailable for the interview, we were not able to survey all of them. We also surveyed non-clients, using a random sampling technique. The number of non-clients was set such that the non-clients/clients ratio in the entire group of four municipalities ranges between 1–1.5. The non-client group has similar characteristics to the clients group: they are also milk producers who mainly sell milk to the two milk buying companies, Pil and Delizia, or make cheese. As mentioned before, while they are non-clients of Sembrar Sartawi, they also have access to several other microcredit institutions and banks.

In total, we surveyed 536 milk producers, of which 89 receive technical assistance, and 447 not.[6] While all farmers with technical assistance are clients of Sembrar Sartawi, our sample also includes 239 farmers that are not Sembrar Sartawi clients (all without technical assistance). We include non-clients as this enables us to conduct to intention to treat (ITT) analyses (see next section), which are less affected by self-selection problems. Table 1 also provides details about the sampling per municipality.

Almost two years after the baseline survey, we conducted a follow-up survey. Due to logistical problems and outmigration, we could not resurvey exactly the same group of milk producers in the endline as we surveyed in the baseline. From the group of clients of Sembrar Sartawi, we were able to resurvey 183 farmers (implying attrition of 60 clients); from the group of non-clients, we were able to resurvey 167 farmers (implying attrition of 126 non-clients). In order to avoid power problems, we also surveyed a group of farmers we didn't survey in the baseline. We especially increased our

Table 1. Baseline sample

	Total	Clients with TA	Clients	Non-clients
Ayo-Ayo	47	4	18	29
Patacamaya	111	17	44	67
Sica Sica	175	26	86	89
Umala	203	42	95	108
Total	536	89	243	293

Note: TA refers to farmers with technical assistance by Sembrar Sartawi from the beginning of the programme.

Table 2. Follow-up sample

	Total	Clients with TA from start (T1)	Clients with TA later (T2)	Clients	Non-clients
Ayo-Ayo	116	2	2	10	106
Patacamaya	98	15	7	37	61
Sica Sica	163	32	23	65	98
Umala	312	58	43	91	221
Total	689	107	75	203	486

Note: Clients with TA later refers to farmers that received technical assistance in a period between baseline and follow-up but not from start.

Table 3. Pooled sample

	Total	Clients with TA from start (baseline)	Clients with TA from start (follow-up)	Clients with TA later (follow-up)	Clients	Non-clients
Ayo-Ayo	54	2	2	1	16	38
Patacamaya	120	14	15	4	74	46
Sica Sica	210	18	27	12	116	94
Umala	316	35	48	23	160	156
Total	700	69	92	40	366	334

Note: Clients with TA later refers to farmers that received technical assistance in a period between baseline and follow-up but not from start.

sample of non-clients, as we targeted already almost all clients of Sembrar Sartawi in the four municipalities. In total we surveyed 689 milk producers in the follow-up, of which 75 received technical assistance in the period between the baseline and the follow-up. In total, 107 farmers used a technician sometime from the start of the technical assistance programme. From the 689 farmers, 203 are member of Sembrar Sartawi and 486 are not. Table 2 provides information about the endline sample. Table 3 does the same for the pooled sample, combining the baseline and follow-up surveys.

4.2. Descriptive statistics

Table 4 provides descriptive information about the baseline sample. A precise definition of each variable can be found in Table A1 in the Appendix. The table shows that farmers live in communities with mean size of 62 households and they are 19 kilometres away from the agency. Fifty-two percent of our respondents are men, they are on average 48 years old, and they completed slightly less than 7 years of education. On average, households are composed of 4 members. In half of the households, Spanish is the

Table 4. Summary statistics (baseline)

	Total sample			No TA			With TA			Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	*N*	*mean*	*sd*	*N*	*mean*	*sd*	*N*	*mean*	*sd*	*(5 vs. 8)*
Male	536	0.524	0.50	447	0.523	0.50	89	0.528	0.50	0.005
Age	536	47.71	14.65	447	47.95	15.03	89	46.51	12.61	−1.441
Household size	536	4.405	2.07	447	4.407	2.06	89	4.393	2.13	−0.014
Spanish	536	0.493	0.50	447	0.470	0.50	89	0.607	0.49	0.137**
Years of education	535	6.912	4.02	446	6.821	4.06	89	7.371	3.76	0.550
Household land (ha)	527	10.20	8.94	440	9.711	8.52	87	12.64	10.53	2.932**
Years of milk production	535	13.43	8.55	447	13.26	8.63	88	14.31	8.15	1.050
Cows owned 3 years ago	534	5.816	5.45	446	5.626	5.47	88	6.784	5.24	1.159*
Altitude (m)	536	3,809	75.34	447	3,808	77.32	89	3,813	64.74	4.670
Distance to agency (Km)	536	19.78	11.75	447	20.38	11.96	89	16.76	10.15	−3.621***
Community size (hhds)	536	62.39	31.46	447	63.81	32.16	89	55.26	26.75	−8.556***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

most spoken language, while in the other half family members mainly speak Aymara, a native language. On average, the milk producers have been engaged in this activity for 13 years. They own 5 cows, one cow less than they owned 3 years prior. This decrease may be partially attributed to the shocks that these farmers faced during 2016. Ninety-nine percent of households own land, 10 hectares on average. It is important to note however that the area of study is very arid and mountainous, and not all land is suitable for cultivation or grazing. On average, respondents consider that their current economic situation is similar to their situation two years ago. Nonetheless, they expect that their economic situation will improve in the next two years. On top of the variables we present in Table 4, we also collected three outcome variables: average daily milk production, monthly revenues, and monthly profits. The average daily production of milk is 19 litres in total. The average monthly revenues from milk and dairy products are 260 USD and the average monthly profits are 158 USD.

In the last column, Table 4 presents the difference in means and the t-test of each variable regarding milk producers with and without technical assistance. We observe that in the group with technical assistance more people speak Spanish and they own more land, which we use as a proxy of wealth. Also, those with technical assistance owned more cows 3 years prior. This group of farmers live closer to the agency and belong to smaller communities compared to the group of farmers without technical assistance. We will take these baseline differences into account into our identification strategy, in the next section. Table A2 in the Appendix presents the same statistics but for the follow-up sample.

5. Identification strategy and power

The main challenge we face is to uncover the causal effect of technical assistance. As farmers cannot be forced to use a technical assistant, measuring impact may be troubled by self-selection biases – the presence of which is hinted by the significant differences in characteristics presented in Table 4 above. It may, for instance, be the case that only the most innovative farmers, who are open to change traditional production methods, decide to use a technical assistant. In this case, a simple comparison of farmers with and without technical assistance would probably overestimate the true impact. However, it is also possible that only farmers without any knowledge about farming practices use a technical assistant. In that case, the impact of technical assistance would probably be underestimated by simply comparing farmers with and without technical assistance. Our analysis is also complicated by the fact that we use observational data, and observe some treatment, without randomisation of assignment to treatment. Moreover, our evaluation started a year after the initiation of the technical assistance programme of Sembrar Sartawi, which implies that our baseline survey is not a ‘true’ baseline. We will deal with potential selection biases by using several quasi-experimental identification strategies, using either cross-sectional regressions or panel regressions. However, we realise that our results may still be affected by endogeneity problems, and hence that our results possibly reflect correlations rather than causal relations.

5.1. Cross-sectional analyses

As only members of Sembrar Sartawi have access to technical assistance, a straightforward method to address selection biases is to conservatively conduct intention to treat (ITT) analyses. Our first identification strategy relies on this idea, and basically compares different outcome variables for members of the MFI and non-members, using a regression framework. That is, we simply estimate ordinary least squares regressions specified as:

$$Y_i = \beta_0 + \beta_1 M_i + \beta_2 X_i + \beta_3 Z_i + \varepsilon_i, \tag{1}$$

where Y is a vector of outcome variables of farmer i, β_0 is a constant; M_i is a dummy variable equal to 1 if the farmer is a member of the MFI, and 0 otherwise; X_i is a vector of farmer characteristics, which are assumed to be exogenous to the technical assistance programme; Z_i is a vector of dummies for the municipalities. β_1 is the coefficient of interest; and ε_i is the error term. β_1 measures the effect of *having the possibility* to hire a technical assistance, irrespective of actually using a technician.

A disadvantage of the ITT approach is that it does not measure the impact of actually using a technician, but having access to one – thus typically underestimating the true impact. Our second identification strategy therefore uses a simple difference in means estimator, i.e. an OLS regression without covariates comparing our treatment and comparison groups:

$$Y_i = \beta_4 + \beta_5 W_i + \varepsilon_i, \tag{2}$$

where W_i is a dummy variable equal to 1 if the farmer received technical assistance from the MFI and 0 otherwise; β_5 is the coefficient of interest; and ε_i is the error term.

To increase the precision of the difference in means estimator, and to control for possible selection bias based on observables, we next include covariates to the previous regression. We refer to this model as the OLS regression with controls:

$$Y_i = \beta_6 + \beta_7 W_i + \beta_8 X_i + \beta_9 Z_i + \varepsilon_i, \tag{3}$$

where all variables are defined above. As an alternative for the OLS with controls regression, our next identification strategy uses propensity score matching (PSM), using the nearest neighbour technique. This method estimates the probability of treatment as $P(W = 1|X)$ and matches one farmer in the technical assistance programme with one farmer out of the programme who has the most similar probability of treatment.

$$ATT_{PSM} = E_{P(X)|W=1}[E[Y(1)|W = 1, P(X)] - E[Y(0)|W = 0, P(X)]] \tag{4}$$

Our final identification strategy of choice uses the Inverse Probability Weighted Regression Adjustment (IWPRA) technique. This method combines inverse probability of treatment weighting (IPW) with separate regression adjustment (SRA). SRA fits different regressions for the treatment and the control groups and uses unweighted means of predicted outcomes to estimate$Y(1)$ for the treatment group and Y(0) for the control group. SRA is specified as:

$$Y_i = \beta_{10} + \beta_{11} W_i + \beta_{12} X_i + \beta_{13} Z_i + \beta_{14} X_i W_i + \beta_{15} Z_i W_i + \varepsilon_i. \tag{5}$$

IPW uses weighted means instead of simple unweighted means to estimate the treatment effects. The approach estimates the propensity scores $P(W = 1|X)$ and obtains the weight as the inverse of the propensity scores $1/P(W = 1|X)$ for the treatment group and $1/(1 - P(W = 1|X))$ for the control group. This implies that higher weights are given when the probability of treatment is low in the treatment group and the probability of treatment is high in the control group. The IWPRA estimator is doubly robust since it combines IPW with SRA, and only one of the two models (treatment or outcome) needs to be correctly specified to obtain consistent estimates.

5.2. Pooled sample regressions

The identification strategies discussed above are applied on both the baseline sample and the endline sample, separately. Note that for the endline regressions (apart from the ITT regressions), we used T1 (did farmers ever received TA) as main treatment variable. Results for T2 are qualitatively the same, and can be obtained on request. We decided to use cross-sectional estimators as the samples for the baseline and the endline differ considerably, and because we do not have a true baseline measurement. However, we will also present estimates using the merged sample.

We conduct three additional estimates. The first estimator is the random effects estimator, which is specified as:

$$Y_{it} = \beta_{20} + \beta_{21} W_{it} + \beta_{22} X_{it} + \beta_{23} Z_{it} + u_{it} + \varepsilon_{it}, \tag{6}$$

where W_{it}, X_{it}, Z_{it} have the same meaning as described above, with exception for the additional subscript t to denote the time dimension of the data. u_{it} represents the between entity error while ε_{it} represents the within entity error. If one has reason to believe that differences across entities have some influence on the dependent variable, then random effects should be used. The random effects estimator provides a consistent estimate provided that one assumes that the entity errors are not correlated with any of the covariates included in the model.

In addition to the random effects model, we also present a between estimator. This estimator makes use of the cross-sectional information in the data by essentially estimating the average of each time period (baseline and endline in this case), and again take the average between the two. In contrast to the random effects estimator above, it does not make specific use of the time series information in the data, but rather treat the two points in time as repeated cross – sections (bars indicate average variables, signifying that time has been averaged out):

$$\overline{Y_{i.}} = \beta_{24} + \beta_{25} \overline{W_{i.}} + \beta_{26} \overline{X_{i.}} + \beta_{27} \overline{Z_{i.}} + \overline{\varepsilon_{i.}}, \tag{7}$$

The final estimator we use is the Mundlak specification (random effects model under Mundlak formulation). The Mundlak specification decomposes the variability in the right-hand side variables by splitting them into two sets of variables: means and deviations from the mean. Basically, the Mundlak specification adds group-means of independent variables which vary within groups. The technique relaxes the random-effects estimator assumption that the observed variables are uncorrelated with the unobserved variables. The Mundlak model is specified as follows:

$$Y_{it} = \beta_{20} + \beta_{21} W_{it} + \beta_{22} X_{it} + \beta_{23} Z_{it} + \beta_{24} \bar{X}_{it} + u_{it} + \varepsilon_{it}, \tag{8}$$

Compared to Equation (8), the group-means of the independent variables, $\bar{X}$has been added. Note that, as our treatment variable (Technical assistance) is hardly changing over time (only a few changes), we have not added group-means for technical assistance. Thus, for the Mundlak estimator, we have assumed that technical assistance is not changing over time.

5.3. Power

Another potential challenge we may be confronted with refers to the sample size. The sample size is important for the power of the analysis, as too low a power may lead to false non-rejections, i.e. false negatives, concluding that there is no effect while in truth there is one. In our case, a power problem may especially result due to the relatively low amount of microfinance clients that receive technical assistance (see Table 1). Recall, however, that we targeted the entirety of clients of Sembrar Sartawi in four municipalities where the MFI had a technical assistance programme. Thus, availability of clients with technical assistance determined the maximum sample size available. Hence, ex-ante formal power analysis in the planning stage of this study were not useful, as it would not have been possible for us to increase the sample in response to low expected power. We are however able to conduct so-called retrospective power analyses. The relevance of retrospective power analysis is controversial, e.g. it is immediately obvious that retrospective power decreases if the significance level increases. In case the estimates suggest a significant effect, the power will be high (and sample size big enough to pick up the effect), while the power will, by definition, be low if there is no significant effect. Thomas therefore states 'calculating power using the observed effect size and variance is simply a way of re-stating the statistical significance of the test'. Rather, calculating minimum detectable effect sizes (using pre-specified power) is helpful, especially if easy to interpret effect size measures are used, such as minimum detectable standardised effect size (*MDES*) measures proposed by Cohen (1988). Therefore, we present some rough retrospective reverse power calculations, using the following formula:

$$MDES = \left(t_\alpha + t_{1-\beta}\right)\sqrt{\frac{1 - R_A^2}{P(1 - P)N}}$$

Where t_α is the t-value of the significance level α, set at 0.05 (one-sided test); $t_{1-\beta}$ is the t value of the pre-specified power β (set at 0.80), R_A^2 is the proportion of pooled unexplained variation predicted by co-variates (set at 0.20 for the models with controls; the 0.20 is based on estimates of the different models, without treatment indicator); N is total sample size and P is the proportion of the sample that is in the treatment group. We conduct 3 power calculations, using the baseline sample: 1) for the ITT estimates with controls, for which the sample size (*N*) is set at 539 and the proportion that has *access* to technical assistance (*P*) at 0.45. The resulting *MDES* = 0.19; 2) for the OLS estimate without controls and 3) for the OLS estimate with controls. For these two estimates, *N* is again set at 539 and *P* at 0.166. The resulting *MDES* equal 0.29 and 0.26, respectively. We have conducted similar calculations using the follow-up sample. The MDES for these estimates are 0.19, 0.26 and 0.24, respectively.

We can gauge the minimum standardised effect sizes implied by our sample by using Cohen's (1988) prescription that values around 0.20 can be considered 'small'. This said, our estimates may be a bit too optimistic as they only refer to the cross-sectional estimators, and assume an 'experimental' design. Adjusting the power calculations for the non-experimental design and for the panel framework is not trivial, but will probably lead to somewhat higher values for *MDES*. Nevertheless, our retrospective reverse power calculations suggest that the relatively small sample size of people receiving technical assistance is not a big concern.

6. Results

We present results for the baseline, endline and merged samples in separate tables. Note that for the PSM estimator as well as the IPW combined with RA, we need to estimate an uptake model of technical assistance. The results of the uptake model are given in the Appendix, Table A3.

As anticipated in section 4.2, the uptake models suggest that farmers with more land, bigger household sizes, and farmers who are longer engaged with milk production are more likely to participate in a technical assistance programme. It also turns out that some 'spatial' variables are important: farmers living at higher altitudes and in some specific municipalities are more likely to participate. All these variables are added as controls or weights to the cross-sectional and panel estimates. In the PSM estimate, they instead form the basis of our propensity score predictors. These propensity scores allow us to match and compare adopters with a representative and weighted sample of credibly similar non-adopters. They can only net out bias deriving from the observed variables. Panel estimates following farmers over time are better suited to net-out unobservable variation, but do not match based on observable differences. We believe that the most robust way to assuage the concern that selection effects are driving our results is to present all the different specifications, and discuss the extent to which results are consistent under them in the next section.

Table 5 presents the results from the baseline cross-sectional analysis.[7] Since all three outcome variables are transformed into natural logarithms we can interpret the coefficients as an approximation of the percentage increase in outcome due to treatment. Column 1 presents the ITT estimates. The estimated effects using the ITT estimator are the most conservative, in line with expectations. In fact, they include Sembrar Sartawi clients with and without technical assistance, and thus only measures effects of having *access to* technical assistance – rather than the effect of its actual utilisation. Daily milk production increases on average by 11%, while monthly revenues increase by 16%. Both are significant at the 5 per cent level. There seems to be no effect on profits using this specification. Note that profits are notoriously difficult to measure due to noise. We then move into the domain of treatment effects on the treated (TOT). Column 2 presents a first naive specification through a simple means comparison, not controlling for selection bias in any way. Farmers accessing technical assistance reveal 32 per cent higher milk production, and over 40 per cent higher revenues as well as profits. Columns 3 and 4 refine this result by taking into account initial differences in observable characteristics (see Table 4), either as control variables (Column 3) or to match the treatment group with a credibly similar comparison sample using nearest neighbour Propensity Score Marching (PSM), as in Column 4. As a result, coefficient sizes go down substantially for all three variables. Finally, Column 5 presents the results of our preferred (TOT) specification, the so called double robust estimator (IPWRA). For this final estimator we find both milk production and monthly revenues to be at 13 per cent and 20 per cent higher respectively, much more in line with the ITT estimator than with the naive difference in means. Profits though increase by 21%.

Next, we present the cross-sectional results for the follow-up sample. This data collection took place almost two years after the baseline, and provides a useful indication about the robustness and trend over time of results found in Table 5. In fact, Table 6 reveals how most results found at baseline are confirmed by the follow-up analysis with remarkable consistency in terms of effect size, and

Table 5. Treatment effects (baseline)

		(1)	(2)	(3)	(4)	(5)
Outcomes (ln)	N	ITT	OLS no controls	OLS with controls	PSM	IPW with RA
Daily milk litres	523	0.1143**	0.3248***	0.1960***	0.1662*	0.1304*
		(0.0536)	(0.08)	(0.0747)	(0.0916)	(0.0702)
Monthly revenues	513	0.1612**	0.4051***	0.2625***	0.2167***	0.1994***
		(0.0648)	(0.0925)	(0.0804)	(0.0840)	(0.0707)
Monthly profits	516	−0.0193	0.2711**	0.0946	0.0167	0.0181
		(0.0785)	(0.11102)	(0.1038)	(0.1142)	(0.0954)

Notes: Number of observations (N) are different for OLS estimator in Column 2, as there are no control variables included. Number of observations there is therefore: Log average litres of milk per day (535), Log monthly revenues (524), log monthly profits (527). The matching technique for PSM is nearest neighbour matching with replacement. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. Treatment effects (follow-up)

		(1)	(2)	(3)	(4)	(5)
Outcomes (ln)	N	ITT	OLS no controls	OLS with controls	PSM	IPW with RA
Daily milk litres	654	0.1270** (0.0614)	0.3409*** (0.0780)	0.2999*** (0.0766)	0.3888*** (0.0894)	0.3108*** (0.0756)
Monthly revenues	588	0.1637** (0.0673)	0.3009*** (0.0857)	0.2566*** (0.0868)	0.4190*** (0.1064)	0.3928*** (0.0857)
Monthly profits	597	0.1365 (0.0838)	0.2105** (0.0995)	0.2128** (0.0999)	0.2866** (0.1215)	0.1673* (0.0932)

Notes: Number of observations (N) are different for OLS estimator in Column 2, as there are no control variables included. Number of observations there is therefore:), Log average litres of milk per day (661), Log monthly revenues (594), log monthly profits (601). The matching technique for PSM is nearest neighbour matching with replacement. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

slightly higher statistical significance. ITT estimated effects in Column 1 confirm that milk production and revenues are respectively around 13 per cent and 16%, only slightly above the estimates made two years prior. Columns 2–5 follow the same pattern: all coefficients are similar if not slightly higher than at baseline. Importantly, this time around also monthly profits exhibit a similar pattern of growth as monthly revenues throughout all specifications (Columns 1 to 5). The ITT model of Column 1 reveals profits to be higher for those with access to technical assistance by almost 17%, whilst according to the IPWRA specification of Column 5 they are a staggering 40 per cent higher.

As mentioned before, none of these estimators perfectly eliminates the potential biases induced by the non-experimental setting we set to analyse. This said, the consistency over time (two separate cross-sections, two years apart) and over different econometric specifications (each addressing potential biases from different angles) finds us confident that the ‘plus’ we set about to investigate had not only statistically significant, but also economically salient effects on those who benefitted from it – even when only considering the most conservative results.

Finally, Table 7 presents a conclusive effort to tease out biases that could lead to smaller lower-bound estimated effects though a panel analysis. Column 1 presents a Random Effects estimator, Column 2 a Between estimator, and finally Column 3 a Mundlak estimator. All three specifications yield very similar estimated effects, ranging between 17–21 per cent higher outcomes for both milk production and revenues. For both, the pooled sample analysis confirms the previous estimates of statistically significant and economically salient effect. Profits are instead found to be positive – being higher for the treatment

Table 7. Treatment effects (pooled sample)

		(1)	(2)	(3)
Outcomes (ln)	N	Random Effects estimator	Between estimator	Mundlak estimator
Daily milk litres	676	0.1778** (0.0743)	0.2059*** (0.0550)	0.1842*** (0.0677)
Monthly revenues	603	0.1754** (0.0886)	0.2126*** (0.0637)	0.1769** (0.0769)
Monthly profits	646	0.0273 (0.1009)	0.1137 (0.0984)	0.0793 (0.0925)

Note: *** p < 0.01, ** p < 0.05, * p < 0.1.

group by between 2 per cent and 11 per cent – but not statistically significant across all three estimators (see next section for a further discussion on this).

7. Discussion and conclusions

We evaluate the technical assistance programme that Sembrar Sartawi offers to its clients in the Province of Aroma, in Bolivia. We collect data from around 600 milk producers who have access to microcredit, and of which several have access to Sembar Sartawi's technical assistance programme. We find that technical assistance correlates positively and significantly with the welfare of farmers. These results are consistent using a variety of cross-sectional and panel estimators. The results strongly support the relevance of microcredit 'plus' models in rural contexts characterised by human capital constraints, where microcredit provision is combined with technical assistance to increase the productivity of the agricultural business. In contrast to most studies on microcredit, which show sobering effects, this study suggests that a combination of credit with technical assistance may be very effective in providing opportunities for income growth.

As is always the case, these large effect sizes will need further research to determine the extent of their external validity. The effect size of technical assistance will dependent on the agronomic field to which it is are applied, and on the ex-ante inefficiency that this certain field has in the context of intervention. In our case, the large increases in milk production and revenues were achieved in a context operating far from their production possibility frontier. The average milk production in our sample is less than 5 litres per cow. Under optimal conditions a dairy cow can be expected to produce an average of 28 litres of milk per day – with peaks above 60. While some of the conditions that lead to such low milk productivity are unavoidable,[8] it is clear that this productivity gap offers huge potential to reduce the inefficiencies, in part. Taking the low initial basis into account, even our highest estimated increase in milk production of 39 per cent does not seem unrealistic. The ensuing increase in revenues confirms that the effect sizes we observe are large and robust, and we have all reason to believe that in contexts with similar efficiency gaps technical assistance as a plus to credit could lead to comparable gains.

The positive effects of technical assistance are supported by a small qualitative study we conducted with eighteen randomly selected milk produces, of which eleven are currently using a technical assistant, three have received technical assistance in the past, and four never had access to technical assistance. All farmers who have or had access to technical assistance were very positive about the services provided by the technical specialist as they were essential for improving milk production. They also expressed that due to the technical assistance, the cattle are healthier not only because the technician has treated diseases, but also because he induced better nutrition, which improved cattle fattening. Our small qualitative analysis also reveals that several farmers remained member of the microfinance organisation, and kept on borrowing from the microfinance organisation, only because this would give them free access to technical assistance. The four farmers who did not have access to technical assistance, expressed their willingness to get access in the future mainly because they thought this service would help to improve sanitation, genetics and nutrition.

This said, of our three outcomes of choice, only revenues and production are robustly significant across all specifications. Monthly profits, the closest proxy to disposable income, reveals more wavering results – it is only significant in one of our estimates. While we are aware that profits are notoriously difficult to measure using survey data – because of the high presence of noise and measurement errors – we prefer to conservatively argue that our study does not have conclusive evidence on the impact of credit plus technical assistance on profits. Moreover, it is plausible that some of the effects we observe are dependent on the very specific conditions of our case study, and will not be reproducible in other areas. For example, it is possible that microfinance institutions that have less access to markets would find it harder to generate such growth in sales as a result of increased production. Similarly, it is imaginable that the scale opportunities in terms of advisory services cannot be reproduced in areas where farmers produce very heterogeneous farm products (instead of only milk as in our case study area). Further research is needed to confirm whether the positive impacts we find also hold in other settings, and experimental designs would help solidify the causality.

It is also important that future research examines to what extent providing technical assistance by MFIs can be self-sustainable and self-financing. While there is consensus that the ‘plus’ component of microfinance – including technical assistance – requires concessional finance to some degree in the initial stages, a proper cost-benefit analysis is worthwhile for the MFIs to expand their businesses. In order to do so, future research should also pay attention to the costs per activity employed by the technical advisors. Finally, a proper cost/benefit analysis should also consider the potential ‘indirect’ benefits of technical assistance for the MFI in terms of borrowers remaining member of the MFI because of the availability of technical assistance, indicated by our qualitative analyses. More in general, further research is needed to understand the implications of technical assistance for the MFI. Do clients that have access to technical assistance indeed stay longer? Do they have lower non-performing loans? When does technical assistance pays back to the company? Knowing this is crucial so that the MFI is able to expand the technical assistance to other branches and at the same time achieve self-sustainability.

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Notes

1. See McKenzie and Woodruff (2014) for a general survey of the effects of business trainings.
2. Consider a production function with complementary inputs: human capital and financial capital (e.g. microcredit). The marginal returns to capital will be higher for farmers with higher human capital (Lucas, 1990), and thus e.g. for those who receive technical assistance. The implication is that the effectiveness of microcredit will be higher if somehow human capital has been improved (see Armendáriz & Morduch, 2010).
3. This section draws from Garcia and Lensink (2019), who provide an extensive survey of the microfinance-plus literature. Our study is most related to this literature.
4. Fixed exchange rate: 1 US Dollar = 6.96 Bolivianos.
5. Qualitative interviews with a subsample of farmers revealed that most could name at least five microfinance institutions which they could access to request financing.
6. It is important to note that we interviewed one person per household, the person responsible for milk production. In some cases, the household member responsible for milk is not the client of Sembrar Sartawi. However, as long as one household member is member of Sembrar Sartawi, access to technical assistance is provided to the entire household, defined as people living under the same roof and eating from the same pot.
7. We have estimated models (2) and (3) in Tables 6 and 7, as well as the three estimates presented in Table 8 also by including a dummy variable for membership of Sembrar-Sartawi to control for potential differences between clients and non-clients. The results, which can be obtained on request, show that the dummy is always insignificant. Moreover, the main results do not change by adding this dummy. For models (1) (3) and (5) in Tables 6 and 7 we couldn’t add this dummy because of perfect collinearity.
8. For example, climatic and breed conditions will not be addressed by a technical assistance programme, other than promoting artificial insemination of more productive breeds, and improving climate-smart feeding practices.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Armendáriz, B., & Morduch, J. (2010). *The economics of microfinance* (2nd ed.). Cambridge, MA: The MIT Press.

Banerjee, A. (2013). Microcredit under the microscope: What have we learned in the past two decades, and what do we need to know? *Annual Review of Economics*, *5*, 487–519.

Banerjee, A., Karlan, D., & Zinman, J. (2015). Six randomized evaluations of microcredit: Introduction and further steps. *American Economic Journal: Applied Economics*, *7*(1), 1–21.

Berge, L. I. O., Bjorvatn, K., & Tungodden, B. (2015). Human and financial capital for microenterprise development: Evidence from a field and lab experiment. *Management Science*, *61*(4), 707–722.

Biosca, O., Lenton, P., & Mosley, P. (2014). Where is the "Plus" in "Credit-Plus"? The case of Chiapas, Mexico. *The Journal of Development Studies*, *50*(12), 1700–1716.

Bruhn, M., & Zia, B. (2013). Stimulating managerial capital in emerging markets: The impact of business training for young entrepreneurs. *Journal of Development Effectiveness*, *5*(2), 232–266.

Bulte, E., Lensink, R., & Vu, N. (2017). Do gender and business trainings affect business outcomes? Experimental evidence from Vietnam. *Management Science*, *63*(9), 2885–2902.

Caretta, M. A. (2014). "Credit plus" microcredit schemes: A key to women´s adaptive capacity. *Climate and Development*, *6* (2), 179–184.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, New Jersey: Lawrence Erlbaum.

Crépon, B., Devoto, F., Duflo, E., & Parienté, W. (2015). Estimating the impact of microcredit on those who take it up: Evidence from a randomized experiment in Morocco. *American Economic Journal: Applied Economics*, *7*(1), 123–150.

Dahal, M., & Fiala, N. (2020). What do we know about the impact of microfinance? The problems of statistical power and precision. *World Development*, *128*, 104773.

De La Cruz, N., Crookston, B., Gray, B., Alder, S., Dearden, K., & De, N. (2009). Microfinance against malaria: Impact of Freedom from Hunger's malaria education when delivered by rural banks in Ghana. *Transactions of the Royal Society of Tropical Medicine and Hygiene*, *103*, 1229–1236.

De Mel, S., Mckenzie, D., & Woodruff, C. (2014). Business training and female enterprise start-up, growth, and dynamics: Experimental evidence from Sri Lanka. *Journal of Development Economics*, *106*, 199–210.

Desai, J., & Tarozzi, A. (2011). Microcredit, family planning programs, and contraceptive behavior: Evidence from a field experiment in Ethiopia. *Demography*, *48*, 749–782.

Drexler, A., Fischer, G., & Schoar, A. (2014). Keeping it simple: Financial literacy and rules of thumb. *American Economic Journal: Applied Economics*, *6*(2), 1–31.

Flax, V. L., Negerie, M., Usman Ibrahim, A., Leatherman, S., Daza, E. J., & Bentley, M. E. (2014). Integrating group counseling, cell phone messaging, and participant-generated songs and dramas into a microcredit program increases Nigerian womenõs adherence to international breastfeeding recommendations. *Journal of Nutrition*, *144*, 1120–1124.

Garcia, A., & Lensink, R. (2019). Microfinance-Plus: A review and avenues for research. In M. Hudon, M. Labie, & A. Sfaraz (Eds.), *Research agenda for financial inclusion and microfinance* (Chapter 9, pp. 111–125). Cheltenham, UK: Edward Elgar.

Giné, X., & Mansuri, G. (2014). *Money or ideas? A field experiment on constraints to entrepreneurship in rural Pakistan* (World Bank Policy Research Working Paper No. 6959).

Halder, S., & Mosley, P. (2004). Working with the ultra-poor: Learning from BRAC experiences. *Journal of International Development*, *16*, 387–407.

Hamad, R., Fernald, L. C., & Karlan, D. S. (2011). Health education for microcredit clients in Peru: A randomized controlled trial. *BMC Public Health*, *11*(51), 1–10.

Huis, M., Lensink, R., Vu, N., & Hansen, N. (2019). Impacts of the gender and entrepreneurship together ahead (GET ahead) training on empowerment of female microfinance borrowers in Northern Vietnam. *World Development*, *120*, 46–61.

Karlan, D., Thuysbaert, B., & Gray, B. (2017). Credit with health education in Benin: A cluster randomized trial examining impacts on knowledge and behavior. *The American Journal of Tropical Medicine and Hygiene*, *96*(2), 501–510.

Karlan, D., & Valdivia, M. (2011). Teaching entrepreneurship: Impact of business training on microfinance clients and institutions. *Review of Economics and Statistics*, *93*(2), 510–517.

Kim, J., Ferrari, G., Abramsky, T., Watts, C., Hargreaves, J., Morison, L., … Pronyk, P. (2009). Assessing the incremental effects of combining economic and health interventions: The IMAGE study in South Africa. *Bulletin of the World Health Organization*, *87*(11), 824–832.

Li, X., Gan, C., & Hu, B. (2011). The welfare impact of microcredit on rural households in China. *The Journal of Socio-Economics*, *40*(4), 404–411.

Lucas, R. E. (1990). Why doesn't capital flow from rich to poor countries? *The American Economic Review*, *80*(2), 92–96.

McKenzie, D., & Woodruff, C. (2014). What are we learning from business training and entrepreneurship evaluations around the developing world? *World Bank Research Observer*, *29*(1), 48–82.

Pronyk, P. M., Hargreaves, J. R., Kim, J., Morison, L. A., Phetla, G., Watts, C., … Porter, J. D. H. (2006). Effect of a structural intervention for the prevention of intimate-partner violence and HIV in rural South Africa: A cluster randomised trial. *Lancet*, *368*, 1973–1983.

Pronyk, P. M., Kim, J., Abramsky, T., Phetla, G., & James, R. (2008). A combined microfinance and training intervention can reduce HIV risk behaviour in young female participants. *AIDS*, *22*, 1659–1665.

Sayinzoga, A., Bulte, E. H., & Lensink, R. (2016). Financial literacy and financial behaviour: Experimental evidence from rural Rwanda. *Economic Journal*, *126*(594), 1571–1599.
Smith, S. C. (2002). Village banking and maternal and child health: Evidence from Ecuador and Honduras. *World Development*, *30*(4), 707–723.
Tarozzi, A., Desai, J., & Johnson, K. (2015). The impacts of microcredit: Evidence from Ethiopia. *American Economic Journal: Applied Economics*, *7*(1), 54–89.
Valdivia, M. (2015). Business training plus for female entrepreneurship? Short and medium-term experimental evidence from Peru. *Journal of Development Economics*, *113*, 33–51.

Appendix

Table A1. List of variables

Variables	Description
Household land (hectares)	Number of hectares owned by household
Years engaged in milk production	Number of years that the respondent has been engaged in milk production
Number of cows 3 years ago	Number of cows that the household owned 3 years ago
Age	Age in years of the respondent
Male	Equal to 1 if the respondent is a man, 0 otherwise
Household size	Number of members living and sharing meals in household
Spanish	Equal to 1 if Spanish is the most spoken language in the household of the respondent, 0 otherwise
Years of education	Number of completed education
Altitude	Altitude of the respondent's house
Distance to agency	Distance in kilometres between the respondent's house and the agency
Community size	Number of households in the community
Average litres of milk produced per day	Daily average of litres of milk produced in total
Average litres of milk produced per day per cow	Daily average of litres of milk produced per cow
Monthly revenues from milk and dairy products	Average monthly revenues during the last 12 months from milk and dairy products in Bolivianos
Monthly profits from milk and dairy products	Average monthly revenues during the last 12 months from milk and products in Bolivianos

Table A2. Summary statistics (follow-up)

	Total sample			Without technical assistance			With technical assistance			Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	*N*	*mean*	*sd*	*N*	*mean*	*sd*	*N*	*mean*	*sd*	*(5 vs. 8)*
Male	689	0.570	0.495	582	0.582	0.494	107	0.505	0.502	−0.078
Age	689	49.63	14.99	582	49.75	15.46	107	48.93	12.20	−0.829
Household size	689	4.187	2.033	582	4.134	2.013	107	4.477	2.130	0.343
Household land (hectares)	688	9.269	9.116	581	9.411	9.578	107	8.498	5.990	−0.914
Years engaged in milk production	689	18.26	12.00	582	18.16	12.22	107	18.75	10.77	0.583
Altitude (metres)	683	3,826	157.8	578	3,828	170.0	105	3,817	53.27	−10.516

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3. Probability of uptake model of technical assistance

Variables	Uptake of TA (baseline)	Uptake of TA1 (follow-up)	Uptake of TA2 (follow-up)
Household land (hectares)	0.0370***	−0.011	−0.015
	(0.0132)	(0.011)	(0.012)
Number of cows owned 3 years ago	0.0197		
	(0.0207)		
Household size	−0.0399	0.095*	0.041
	(0.0661)	(0.056)	(0.064)
Age	−0.0151	−0.001	−0.004
	(0.0117)	(0.009)	(0.010)
Male	−0.368	−0.303	−0.246
	(0.304)	(0.238)	(0.258)
Spanish	0.354		
	(0.275)		
Years of education	0.0191		
	(0.0378)		
Years engaged in milk production		0.016*	0.019*
		(0.010)	(0.011)
Altitude (metres)	0.00451**	0.006***	0.003
	(0.00177)	(0.002)	(0.003)
Municipality 2 (Patacamaya)	−0.0745	3.177***	1.809**
	(0.796)	(0.838)	(0.875)
Municipality 3 (Sica Sica)	0.952	3.517***	2.583***
	(0.739)	(0.838)	(0.829)
Municipality 4 (Umala)	0.972	3.601***	2.704***
	(0.717)	(0.823)	(0.851)
Constant	−17.89**	−29.444***	−15.187
	(7.192)	(9.068)	(10.720)
Observations	524	682	682
Model accuracy (area under ROC curve)	0.7175	0.678	0.673

Note: We model the probability of treatment, that is, the probability that a farmer uptakes technical assistance. We use these results (probabilities) to perform two estimation methods: PSM, and IPW combined with RA. We estimate this model based on exogenous characteristics of farmers, which influence the decision of farmers to take up this service, but that are not affected by technical assistance. We estimate a binary model, assuming a logistic distribution. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Probit estimates. Dependent variable is a zero/one dummy, with a one if the farmers has used a technician. TA1 refers to having used a technician from start of programme; TA2 refers to having used a technician between baseline and endline.