Can Mobile Technology Improve Female Entrepreneurship? Evidence from Nepal*†

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Abstract

Gender norms may constrain the ability of women to develop their entrepreneurial skills, particularly in rural areas. By bringing entrepreneurial training to women rather than requiring extended time away from home, mobile technology could open doors that would otherwise be closed. We randomly selected Nepali women to be trained as veterinary service providers known as community animal health workers. Half of the selected candidates were randomly assigned to a traditional training course requiring 35 consecutive days away from home, and half were assigned to a hybrid distance learning course requiring two shorter stays plus a tablet-based curriculum to be completed at home. Distance learning strongly increases women's ability to complete training as compared to traditional training. Distance learning has a larger effect than traditional training on boosting the number of livestock responsibilities women carry out at home, while also raising aspirations. Both training types increase women's control over income. Our results indicate that if anything, distance learning produced more effective community animal health workers.

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1 Introduction

Although the majority of the developing world's small-scale entrepreneurs are women (Jayachandran, 2021), gender norms may limit women's ability to fully exploit entrepreneurial opportunities (Jayachandran, 2020). Constraints stemming from gender norms could be compounded in rural areas. For example, rural women might not be able to travel to business training because of restrictions on mobility or responsibilities at home, exacerbated by long distances from training centers. These constraints could potentially be loosened by mobile phones or tablet computers. Rather than requiring that women be far away from home for extended periods of time, or having implementing agencies keep staff in disperse rural areas for extended periods of time, information and communication technology could bring training to women. If training is for occupations that are seen as appropriate for women and can be practiced locally, training through mobile technology could open doors to success for rural female entrepreneurs that would otherwise be closed.

We use a randomized control trial to compare the effectiveness of classroom-based business training and hybrid distance training for women, where hybrid distance training substitutes two-thirds of classroom time with training on a tablet. The purpose of training is to earn certification as a Community Animal Health Worker (CAHW), i.e., providers of primary animal health care in rural communities. Our study context is rural Nepal, where livestock and poultry greatly outnumber the human population and are an important source of income and nutritious food.

We estimate intent-to-treat effects (ITTs) and local average treatment effects (LATEs) of each training modality on training completion, income, savings, livestock knowledge, and livestock responsibilities at home, and compare the estimated treatment effects of each training type relative to one another. The LATE estimates measure treatment effects on women who would take their assigned form of CAHW training were it offered to them, and not otherwise. We find that assignment to hybrid distance training rather than traditional training has a large and statistically significant positive effect on the probability of becoming a CAHW, raising training completion from 29% to 52%. This effect is especially large for women with infant children or whose household has sent a migrant. Hybrid distance training strongly increases livestock knowledge while increasing livestock management responsibilities at home. Although ITTs on knowledge and management are consistently larger for hybrid distance learning, this appears to be because of higher training completion rates, as there is no clear pattern of one training system having greater LATEs than the other.

We find no significant effects on total income at the household level or among women in the sample. When examining binary income measures, we find that hybrid distance training raises the probability that a woman solely controls at least some income. In addition, quantile regression results suggest that training raised joint control over income for women below the median. The intervention may not have raised average incomes because of Covid-19 mobility restrictions, as trainees reported having substantially more client visits the month prior to government-instituted lockdown as compared to the month before follow-up interviews. Effects on savings are imprecisely estimated.

The fact that LATEs are similar across training types does not imply that both training systems are equally effective. For example, hybrid distance learning could lead to women with less capacity to work as CAHWs completing training, but this effect could be canceled out by distance training being more effective than traditional training. We attempt to disentangle the effects of selection from training modality by imputing the average outcomes that traditionally-trained CAHWs would have obtained had they completed hybrid distance training. We then compare average observed outcomes among traditionally-trained CAHWs to their imputed distance-training outcomes. Our results suggest traditionally-trained CAHWs would have performed more livestock tasks at home, visited more clients, and offered more client services had they completed distance training. This result is tempered by the fact that we cannot reject the null for an overall index of CAHW performance.

We contribute to the literature on applications of mobile technology for agriculture in rural areas of developing countries. To date, this literature has focused on using SMS messaging to facilitate access to price information or improve farmer management practices. Messaging to improve price information has met with mixed success, with some interventions showing positive impacts on prices received (Courtois and Subervie, 2014; Nakasone, 2014; Hildebrandt et al., 2020) and others demonstrating that effectiveness is undermined when prices are for markets that are not used by small farmers (Fafchamps and Minten, 2012; Mitra et al., 2018). The literature on using mobile technology to promote improved management practices also shows mixed results, sometimes showing large impacts on yields (Casaburi et al., 2014) or input use (Cole and Fernando, 2020) and others showing null effects (Fafchamps and Minten, 2012); see Fabregas, Kremer, and Schilbach (2019) for a meta-analysis of the existing literature. Our study differs from this body of literature in three ways. First, we focus on livestock rather than crop agriculture. Second, our intervention is built around training rural service providers, rather than giving information to farmers that would normally be delivered by an extension agent. Third, the technology evaluated in our study is more sophisticated than simple SMS messaging.

We also contribute to the literature on entrepreneurial training in developing countries. As with the traditional training modality studied here, entrepreneurial training is usually classroom-based. A recent summary of existing randomized trials shows that classroom-based entrepreneurial training increases revenue by 5.6% and profits by 12.1%, on average (McKenzie et al., 2021). The same literature review summarized four randomized trials of entrepreneurial training programs exclusively for women and finds widely varying impacts on sales and profits. In contrast to our study, entrepreneurial training programs tend to focus on general skills that could be applied to any business, rather than technical training for a specific profession (McKenzie et al., 2021).

We also add to a small literature evaluating the effects of alternative delivery methods for entrepreneurial training. Acimovic et al. (2020) use a randomized control trial in Tanzania to study whether in-person training or SMS messages affect the amount of cash on hand held by mobile money agents; available cash is an important constraint on the ability to complete mobile money transactions. They find that in-person training and explicit recommendations (as opposed to historical data on transaction volumes) are necessary for changes in agent behavior. Jin and Sun (2021) randomly assign two million retailers to online training meant to improve performance in e-commerce and find that training increases revenue by 6.6%. Jin and Sun (2021) report that 24% of firms attempted at least one training task while 12.6% completed at least one task, and that participation dropped quickly over time; these participation rates are significantly lower than what is usually found for classroom-based training (see table 3 in McKenzie and Woodruff (2013)).

Lastly, we contribute to the literature on impacts of educational technologies in developing countries. Several randomized trials have looked at the impact of providing handheld devices on educational outcomes among children, finding mostly positive results. Beg et al. (2019) study the effects of two separate ways of distributing tablets with multimedia math and science content to middle-school classes in Pakistan: to math and science teachers only, and directly to students as well as science teachers. In the teacher-distribution treatment, teachers were trained on how to integrate the tablets into their curriculum, and classrooms received LED screens onto which tablet content could be projected. Beg et al. (2019) find that distributing tablets to teachers strongly boosted student achievement, while giving tablets to students had the opposite effect.

Several other education technology studies are summarized in Rodriguez-Segura (2021). Habyarimana and Sabarwal (2018) find that e-readers with instructional content increase reading and math scores in Nigeria but only for students without access to textbooks. Piper et al. (2016) use a randomized control trial in Kenya to compare distribution of e-readers to students, tablets for teachers, and tablets for tutors. They find that all three treatments had significant impacts on English and Kiswahili scores, with tutor tablets being the most cost effective. Pitchford (2015) randomized students in Malawi into groups receiving tablets with mathematics content, tablets without mathematics content, and standard face-to-face instruction, with all three groups receiving face-to-face instruction as well. Tablets plus mathematical content significantly increased test scores relative to the other two treatments. Our study is similar to Pitchford (2015) and Beg et al. (2019) in that all treated individuals received at least some in-person instruction, but we focus on vocational training for adults rather than schooling for children.

In what follows, we first present the background for our intervention and our experimental design. We then describe our data and show balance across treatment assignments. We move on to describing our empirical approach and presenting our main results. We then conduct exploratory analyses to unpack our main results before ending with a brief conclusion.

2 Background and Intervention

Nepal has a total population of approximately 29 million people, while livestock and poultry number approximately 28 million and 83 million, respectively (Statistics Section, Department of Livestock Services, 2018). Livestock account for 11% of GDP and 27% of agricultural GDP (Bhaatarai et al., 2019). Heifer International Nepal (HIN), the research team's main implementing partner, has worked to support the livestock sector in Nepal since 1996. As part of its programming, Heifer helps women in rural households form self-help and savings groups. After completing extensive training on animal management, entrepreneurship, and values (e.g., self-reliance, gender equity, spirituality), households receive livestock as long as they agree to "pass on the gift", i.e., give offspring of their transferred livestock to a subsequent graduate of Heifer training (Janzen et al., 2020). Eventually, Heifer helps the self-help groups aggregate into livestock producer cooperatives, focused on either meat goats or dairy farming. Currently about 250 such livestock cooperatives exist, with an average membership of around 1,000 women.

In order to support its cooperatives, Heifer subsidizes the training of "Community Animal Health Workers" (CAHWs), para-veterinarians offering basic animal health services.

CAHWs are sometimes described as "barefoot vets" (Halpin, 1981; Leyland and Catley, 2002), terminology that likely derives from China's use of "barefoot doctors" to make basic health services widely accessible (Chetley and Barnard, 1995). Descriptive evidence suggests that CAHWs are effective in epidemiological surveillance and boosting vaccine rates, and that they may positively impact economic outcomes for livestock keepers (Bugeza et al., 2017; Catley et al., 2004; Mugunieri, Irungu, and Omiti, 2004).

CAHW training covers a government-approved curriculum with topics such as breeds, anatomy, drug administration, bookkeeping, animal husbandry, disease symptoms and diagnostics, castration, and animal fodder production. At the conclusion of training, participants must pass a certification exam and register with their local municipality to formally work as a CAHW. HIN pays for the training fees of CAHWs supporting its cooperatives, and also provides each CAHW with a startup kit including a microscope, drugs, fodder seeds, and a castrator. The total cost of traditional classroom-based training is $428 per trainee.

To train as a CAHW in the usual way, trainees live in a dormitory at a training center for 35 days. The days are spent alternating between classroom time and hands-on training with livestock. The literature on women's time use and empowerment suggests that staying outside the home for an extended period of time might prevent many from training as CAHWs (Jayachandran, 2020). Throughout the world, women are expected to do the majority of housework and childcare (Bittman et al., 2003; Sayer, 2005). Families might be hesitant to allow women to spend the night outside of their village (Dean and Jayachandran, 2019). GPS data from our baseline survey indicate that sample members are an average of 100 kilometers from the nearest training center. HIN reports that 43% of individuals trained as CAHWs with its support are female. At first glance this seems to be a high percentage, but it is less impressive when one considers that all members of the hundreds of cooperatives formed by Heifer are women. There are no national statistics available that disaggregate total CAHWs by sex.

Given the constraints listed above, the research team, HIN, and the Government of

Nepal's Ministry of Agriculture developed a hybrid distance learning system for training CAHWs. Hybrid distance learning requires that trainees leave their villages and stay at a training center with other trainees for a five-day orientation where they meet their instructors, learn how to use the tablets, and are told how they will be monitored by training center personnel. Trainees then return to their villages where they have 30 days to complete the digitized version of the CAHW curriculum. Originally the amount of time spent at home was to be 20 days, but the training centers and HIN agreed to add a ten day grace period after some initial technical difficulties with the tablets. Trainees are monitored through phone calls with training center personnel. All trainees reported speaking with training personnel at least once per week. The tablets have a wireless internet connection, and the training platform includes a virtual "discussion board" where individuals ask questions that are visible to the rest of their cohort. 77% of distance trainees reported using the discussion board. After spending 30 days at home, trainees return to the training center for ten consecutive days to conduct practical exercises and sit for final examinations. At the conclusion of the CAHW course, a trainee who passes her final examinations can register with the government as an official CAHW. There is no difference in the level or type of qualification received based on training type. Without the tablet, the total cost of hybrid distance learning is $300 per trainee, with cost savings relative to traditional training coming from room and board at the training center. With the tablet, the total cost is 428$.

Whether offering distance learning will increase the number of women who are able to become CAHWs depends on what the binding constraints are. If the key constraint is limited mobility or household responsibilities that prevent women from staying overnight outside the home, then distance learning could be effective in raising training completion rates. If the constraint is available time, then it might be effective or it might not. Studying at home with a tablet still takes time, although it is more flexible. If the key constraint is that being a CAHW is seen as inappropriate for women, perhaps because it might require interacting with male clients (Boudet, Petesch, and Turk, 2013), then distance learning would likely make no difference. Distance learning might present its own constraints if women are less comfortable training on a tablet without constant instructor guidance, relative to learning from printed material.

Even if distance learning does relax constraints on training completion, it could result in lower-quality trainees for several reasons. If distance learning is relatively less costly from the perspective of trainees and their households, then lower quality trainees might find it worthwhile to complete distance training whereas they would not under traditional training. But this effect is ambiguous, as lower costs in terms of time away from home would be offset by higher household costs of feeding and housing trainees; the latter costs are paid for by HIN while trainees are at the training center. Even if there are no differences in average candidate quality prior to training, the training modalities themselves could affect candidate quality. Learning in groups at the training center could be more effective than training at home if trainees pressure each other to do well. Splitting up hands-on and classroom training could be less effective than regularly reinforcing classroom training with hands-on practice. It may be better to ask and have answered questions in the moment, as would be the case at the training center. On the other hand, distance learning could encourage trainees to be more independent and give them confidence in a job that requires individual service to clients. The distance learning platform also includes multi-media and interactive self-assessment tools that could boost learning relative to learning from a textbook.

3 Experimental Design

3.1 Sample and baseline data collection

A total of 104 HIN cooperatives participated in the study. Officers at each of the 104 cooperatives were asked how many additional CAHWs they would like trained to operate in their area. Officers were not told about the hybrid distance learning platform prior to joining the study. In each of these cooperatives, leadership was asked to nominate women who met the following criteria to potentially be trained as a CAHW.

1. Completion of 8^{th} grade (imposed by the Government of Nepal)

2. Between 20-35 years old (to have a potentially long career as a CAHW ahead of them)

3. Married (because a woman who marries will typically move to her husband's village)

The second and third criteria were not always followed by the cooperatives, but women selected outside of those criteria remained in the study. All women on the lists initially provided by the cooperatives were included in the baseline survey, which took place from September 5 to October 8, 2018, and included 420 observations. In the baseline survey we asked candidates about their interest in both distance learning and traditional training courses. The 43 candidates with no interest at all were dropped from the sample at this point, reducing the sample to 377 candidates. We then needed to refine the sample so that the number of candidates from each cooperative was twice the number of CAHWs requested by the cooperative (usually one but sometimes two or three). If cooperatives with longer lists of candidates were less selective than cooperatives with short lists, average quality of candidates in the control group would potentially be worse than average quality in the treatment group.

In some cases cooperatives had too few candidates. We asked these cooperatives to add to their list so that there were twice as many as CAHWs requested. 46 additional candidates were added in this way and surveyed from January 5 to February 12, 2019. In other cases cooperatives nominated too many women. For these cooperatives we limited the number of candidates in a way that would preserve those most likely to enroll based on their stated interest. After adding and trimming candidates in this way we were left with 300 candidates across the 104 cooperatives.

3.2 Treatment assignment

Treatment was assigned using a two-stage randomization over the 104 cooperatives and 300 candidates described above. First, we randomly assigned each cooperative to distance learning (52 cooperatives) or traditional training (52 cooperatives). Cooperatives were stratified using bins determined by cooperative-level variables (geographic zone, median household income, and median dependency ratio). Second, we randomly assigned which candidates within a cooperative were to receive training of the type assigned to their cooperative, stratifying by cooperative and individual income. The remaining candidates in each cooperative would serve as controls.

The development of the intervention and experimental design are described in figure 1. Of the 77 candidates recruited to participate in distance training, just over half completed the training (40 candidates, or 52%). Of the 73 candidates recruited to participate in the TT training, just under one third (21 candidates, or 29%) completed the training. In addition, we observe some non-compliance by control individuals. Two candidates in the control group from distance learning cooperatives managed to sign up for and complete distance training. Four candidates from traditional training who were not assigned to treatment cooperatives managed to sign up for and complete traditional training.

Follow-up data were collected in January 2021, 18 months after the end of training. The research team put off follow-up data collection as long as possible to try and wait out Covid-19 restrictions, but eventually decided to run the survey by phone. The delay should have allowed trainees adequate time to establish their businesses. Enumerators were able to follow up with 92% of the original sample. Conditional on the cluster-level assigned training modality, attrition is almost identical by treatment status. In distance learning cooperatives, 71 of 77 controls and 72 of 77 women assigned to treatment were re-interviewed. In traditional training cooperatives, these same figures are 66 of 73 and 67 of 73, respectively. The follow-up sample is too balanced by treatment status to estimate bounds on estimated impacts (Lee, 2002).

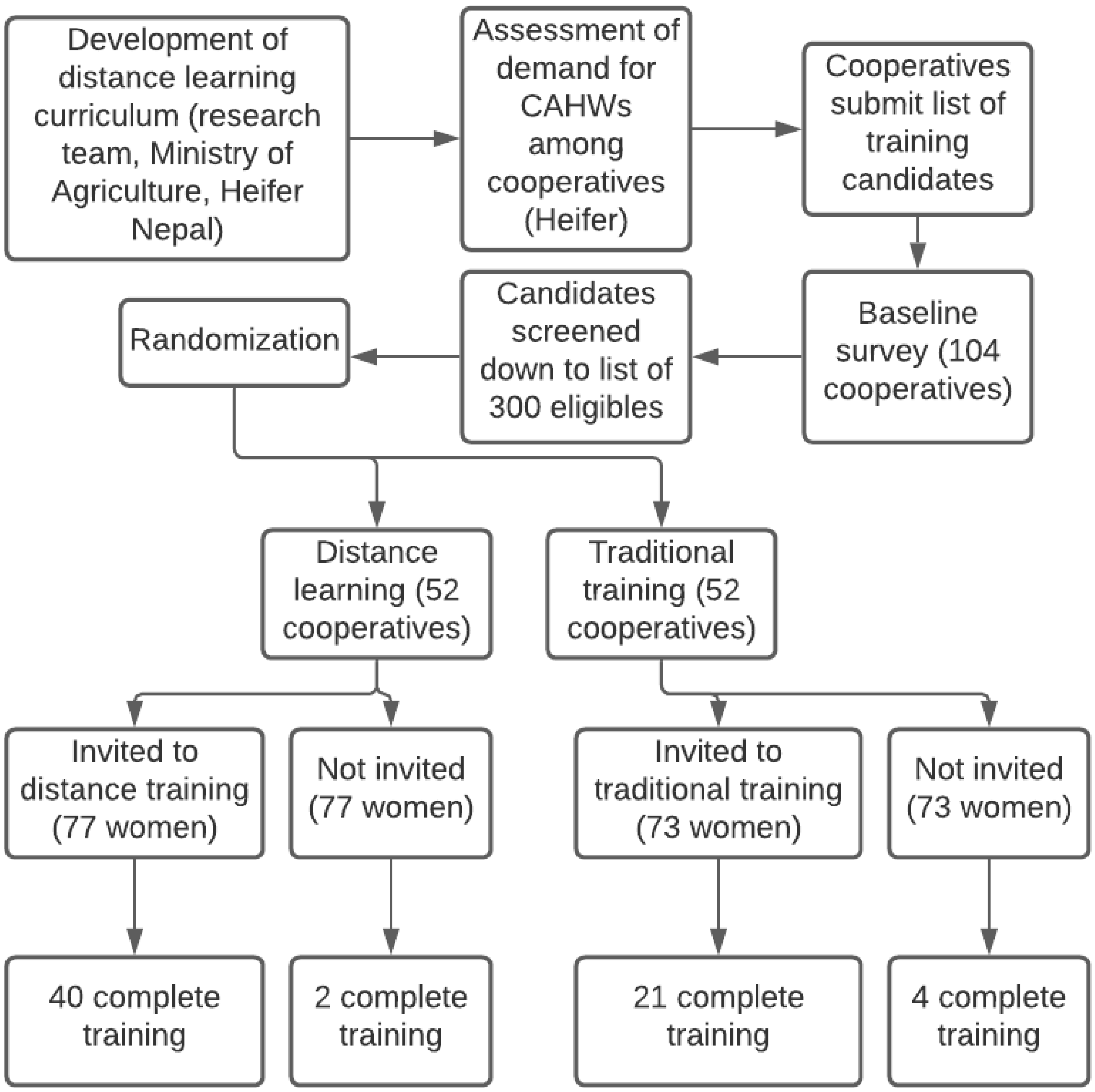

Figure 1: Development of Distance Learning and Experimental Design

3.3 Summary Statistics and Balance

Table 1 shows summary statistics and balance for the sample used in our analysis. We find no significant differences in means when comparing either treatment group to the control group, or the treatment groups to one another.

Table 1: Summary Statistics and Balance

Variable	(1) Distance learning Mean/SD	(2) Traditional training Mean/SD	(3) Control Mean/SD	Difference (1)-(2)	(1)-(3)	(2)-(3)
Total household income	3,665.389	3,311.558	3,319.038	353.831	346.351	-7.480
	(2,822.429)	(2,663.332)	(2,824.011)			
Woman's total income	191.944	155.493	117.898	36.452	74.047	37.595
	(552.024)	(480.248)	(451.724)			
Woman earns some non-farm income (0/1)	0.069	0.045	0.058	0.025	0.011	-0.014
	(0.256)	(0.196)	(0.231)			
Woman solely controls some income (0/1)	0.236	0.239	0.226	-0.003	0.010	0.013
	(0.436)	(0.430)	(0.363)			
Woman's jointly controlled income	1,281.601	1,070.842	1,056.289	210.759	225.312	14.553
	(1,851.914)	(1,427.355)	(1,494.954)			
Livestock knowledge test, percent correct	63.056	55.224	60.146	7.832	2.910	-4.922
	(22.283)	(22.719)	(24.213)			
Percent correct, easy	88.889	79.104	85.766	9.784	3.122	-6.662
	(25.103)	(33.051)	(30.698)			
Percent correct, intermediate	24.306	19.403	22.628	4.903	1.678	-3.225
	(30.111)	(26.801)	(28.915)			
Percent correct, hard	88.889	79.104	83.942	9.784	4.947	-4.837
	(31.253)	(42.146)	(36.059)			
Age (years)	30.153	28.522	28.927	1.630	1.226	-0.405
	(6.736)	(7.429)	(7.157)			
Woman's education (years)	10.514	10.269	10.599	0.245	-0.085	-0.330
	(1.689)	(1.678)	(1.321)			
Married (0/1)	0.847	0.731	0.796	0.116	0.052	-0.064
	(0.379)	(0.438)	(0.451)			
Household size (count)	5.986	6.493	6.292	-0.506	-0.306	0.201
	(2.754)	(3.104)	(2.681)			
Household has a migrant (0/1)	0.514	0.507	0.511	0.006	0.003	-0.003
	(0.468)	(0.506)	(0.524)			
Belongs to high caste (0/1)	0.431	0.433	0.431	-0.002	-0.000	0.002
	(0.563)	(0.607)	(0.540)			
Age of household head (years)	47.625	47.925	47.219	-0.300	0.406	0.706
	(11.550)	(12.306)	(13.510)			
Household owns livestock (0/1)	0.958	0.955	0.971	0.003	-0.012	-0.016
	(0.199)	(0.196)	(0.206)			
High interest in distance learning (0/1)	0.819	0.836	0.803	-0.016	0.017	0.033
	(0.353)	(0.394)	(0.443)			
High interest in traditional training (0/1)	0.764	0.701	0.730	0.062	0.034	-0.028
	(0.391)	(0.540)	(0.472)			
High interest in both (0/1)	0.722	0.672	0.672	0.051	0.051	0.000
	(0.402)	(0.553)	(0.484)			
Owns a smartphone (0/1)	0.833	0.866	0.818	-0.032	0.016	0.048
	(0.361)	(0.371)	(0.391)			
Has social media account (0/1)	0.750	0.731	0.737	0.019	0.013	-0.006
	(0.419)	(0.421)	(0.454)			
Observations	72	67	137			
Clusters	49	47	96			

Notes: * p <0.10, ** p <0.05, *** p <0.01. All regression for t-tests include stratum fixed effects. All monetary variables are in dollars.

4 Empirical Approach and Results

4.1 Intent-to-Treat Effects and Local Average Treatment Effects

We estimate intent-to-treat effects (ITTs) for each training modality as well as differences in ITTs by training type. For ITT estimates, we have:

$$y_{isc} = \beta_0 + \beta_1 INV_{isc} \times TT_c + \beta_2 INV_i \times DL_c + \beta_3 y^0_{isc} + \lambda_s + \varepsilon_{isc} \qquad (1)$$

where i, s, and c index candidate, stratum, and cooperative, respectively; y_{isc} is the outcome observed at follow-up; INV_{isc} is an indicator equal to one for women invited to training; TT_c is an indicator for being in a traditional training cooperative; DL_c is an indicator for being in a distance learning cooperative; y^0_{isc} is the baseline outcome (included when available); and λ_s is a stratum fixed effect. We report estimates of the ITT effects, β_1 and β_2, and their difference, while clustering standard errors at the cooperative level (Abadie et al., 2017). We estimate the specification given in equation 1 as well as a model augmented by a covariate vector, X_{isc}, chosen by the post-double selection lasso algorithm (PDS LASSO) described in Belloni, Chernozhukov, and Hansen (2014). The PDS LASSO algorithm retains covariates in the model that are strongly correlated with the outcome or with either treatment, conditional on the baseline outcome and stratum fixed effects, while forcing coefficients on other covariates to zero. The LASSO algorithm limits the number of covariates retained in the model by constraining the sum of the absolute values of the regression coefficients, after normalizing all covariates to be on the same scale. See Belloni et al. (2012) for a derivation of the formula used to set the value of the tuning parameter governing the constraint on the regression coefficients.

The effect of training itself is arguably of greater interest than the impact of being offered treatment. Therefore we estimate local average treatment effects (LATEs) of each training type. The LATE of a given training type is the average treatment on "compliers", i.e., women who would complete a particular type of training only if invited to it. The

LATE of a binary treatment is identified under the assumption that treatment assignment is exogenous and that there are no "defiers", i.e., no one in the population always does the opposite of their treatment assignment (Angrist and Imbens, 1995). Since very few members of the control group completed training, we expect that the LATEs will closely approximate the average treatment effect on the treated. Our estimating equations for the LATEs are given below:

$$y_{isc} = \alpha_0 + \alpha_1 \widehat{CAHW}_{isc}^{TT} + \alpha_2 \widehat{CAHW}_{isc}^{DL} + \alpha_3 y_{isc}^0 + \eta_s + \varepsilon_{isc} \quad (2)$$

where $\widehat{CAHW}_{isc}^{j}$ for $j \in \{TT, DL\}$ is the fitted value from the following regression:

$$CAHW_{isc}^{j} = \gamma_0 + \gamma_1 INV_{isc} \times TT_c + \gamma_2 INV_{isc} \times DL_c + \gamma_4 y_{isc}^0 + \phi_s + \omega_{isc} \quad (3)$$

We report estimates of α_1 and α_2 as well as their difference and cluster standard errors by cooperative. In addition to equations 2 and 3, we estimate models that include a covariate vector chosen by the PDS LASSO algorithm.

4.2 Main Results

We estimate ITTs and LATEs for indicators of training completion, livestock practices, livestock knowledge, income, savings, and aspirations. When estimating impacts on income, we use binary indicators for categories with few non-zero entries, as means of these income types tend be dominated by outliers. Results are given in tables 2, 3, 4, 5, and 6.

As shown in table 2, an invitation to either type of training has a large and statistically significant effect on becoming a CAHW. Being assigned to distance learning raises the probability of becoming a CAHW by nearly 30 percentage points, or about 55% relative to women assigned to traditional training. Note that all but one candidate who enrolled in CAHW training was eventually certified as a CAHW, so that impacts on training completion are driven by enrollment rather than differences in completion rates conditional on enrollment.

Table 2: Impact on Completion of Training by Training Type

	Completed training
ITT, distance	0.493***
	(0.094)
ITT, traditional	0.193*
	(0.101)
Difference	0.299**
	(0.138)
ITT PDS LASSO, distance	0.493***
	(0.094)
ITT PDS LASSO, traditional	0.193*
	(0.101)
Difference	0.299**
	(0.138)
Control mean	0.044
Observations	276

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard in parentheses. All specifications include stratum fixed effects.

ITTs for indicators of livestock knowledge and at-home management are consistently larger and more precisely estimated for distance training, as indicated in table 3. For knowledge indicators, the pattern with respect to the size of point estimates disappears once we consider LATEs. But effects for distance training continue to be more precisely estimated. LATEs for management indicators are larger and more precise for distance training, with a significantly higher LATE for distance learning with respect to easy management practices at home. In general, treatment effects are not significantly different by training modality. The lone exception to this rule is "Number of easy health practices on own livestock", where all differences in treatment effects are significant except for LATEs estimated using the PDS LASSO.

Impacts on income and savings are imprecisely estimated in general, as shown in tables 4 and 5. But there is evidence that distance learning increased women's control over income. In particular, the LATE estimate for "Women's annual solely-controlled income (0/1)" is statistically significant for distance learners in three of four regression specifications. There

Table 3: The Impact of Training on Livestock Knowledge and Management by Training Type

	Percent correct, easy livestock questions	Percent correct, intermediate livestock questions	Percent correct, hard livestock questions	Overall score	Number of easy health practices, own livestock	Number of easy health practices, own livestock
ITT, distance	9.884**	22.070***	6.635*	12.814***	1.130***	0.899**
	(4.789)	(8.076)	(3.931)	(4.437)	(0.376)	(0.349)
ITT, traditional	3.724	6.731	4.327	5.011	-0.092	0.261
	(4.195)	(8.715)	(3.963)	(3.518)	(0.369)	(0.374)
Difference	6.160	15.340	2.308	7.802	1.223**	0.638
	(6.329)	(11.896)	(5.632)	(5.635)	(0.527)	(0.511)
ITT PDS LASSO, distance	9.884**	22.070***	6.635*	12.814***	1.130***	0.899***
	(4.747)	(8.006)	(3.897)	(4.399)	(0.373)	(0.346)
ITT PDS LASSO, traditional	3.724	6.731	4.327	5.011	-0.092	0.261
	(4.159)	(8.640)	(3.929)	(3.488)	(0.367)	(0.371)
Difference	6.160	15.340	2.308	7.802	1.223**	0.638
	(6.275)	(11.793)	(5.583)	(5.586)	(0.524)	(0.508)
LATE, distance	20.115***	44.763***	13.370**	25.984***	2.294***	1.824***
	(6.476)	(11.591)	(5.354)	(5.884)	(0.541)	(0.456)
LATE, traditional	19.072	34.764	22.495	26.003*	-0.478	1.348
	(15.829)	(31.012)	(16.087)	(14.534)	(1.369)	(1.257)
Difference	1.043	9.999	-9.125	-0.019	2.772*	0.476
	(16.992)	(33.108)	(17.036)	(15.723)	(1.472)	(1.337)
LATE PDS LASSO, distance	20.115**	44.763***	13.370*	25.984***	2.294***	1.824***
	(9.313)	(16.669)	(7.700)	(8.462)	(0.776)	(0.655)
LATE PDS LASSO, traditional	19.072	34.764	22.495	26.003	-0.478	1.348
	(22.763)	(44.599)	(23.135)	(20.901)	(1.965)	(1.804)
Difference	1.043	9.999	-9.125	-0.019	2.772	0.476
	(24.437)	(47.613)	(24.500)	(22.611)	(2.113)	(1.919)
Control mean	87.348	60.097	52.068	65.856	1.715	0.993
Observations	276	276	276	276	276	276

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses. All specifications include stratum fixed effects and the de-meaned baseline outcome. All monetary variables are in dollars. Livestock knowledge was measured using three sets of three questions, distinguished by difficulty level. Most knowledge questions had multiple correct answers, and the score within a given level of difficulty was calculated as the number of correct answers divided by the total number of possible correct answers. The number of livestock practices performed at home was calculated by asking whether 14 separate practices were performed by the respondent in the past 12 months, split between six easy and eight difficult tasks.

Table 4: The Impact of Training on Income by Training Type

	Total household annual income	Woman's total annual income	Woman's non-farm annual income (0/1)	Woman's annual solely controlled income (0/1)	Woman's annual jointly controlled income
ITT, distance	124.905	28.085	0.014	0.151	142.534
	(580.049)	(187.741)	(0.103)	(0.099)	(464.243)
ITT, traditional	404.547	97.436	0.109	-0.065	-37.549
	(670.444)	(312.017)	(0.080)	(0.128)	(416.703)
Difference	-279.642	-69.351	-0.094	0.216	180.083
	(886.474)	(365.778)	(0.130)	(0.163)	(636.717)
ITT PDS LASSO, distance	124.905	28.085	0.014	0.164*	142.534
	(574.013)	(186.128)	(0.102)	(0.094)	(460.256)
ITT PDS LASSO, traditional	404.547	97.436	0.109	-0.086	-37.549
	(663.468)	(309.338)	(0.079)	(0.119)	(413.125)
Difference	-279.642	-69.351	-0.094	0.250	180.083
	(877.250)	(362.637)	(0.129)	(0.154)	(631.249)
LATE, distance	267.613	54.512	0.029	0.306**	294.859
	(796.843)	(262.550)	(0.143)	(0.140)	(652.703)
LATE, traditional	2036.462	501.468	0.565*	-0.341	-200.833
	(2328.851)	(1078.621)	(0.316)	(0.428)	(1512.662)
Difference	-1768.849	-446.956	-0.535	0.647	495.692
	(2442.557)	(1118.029)	(0.348)	(0.452)	(1688.582)
LATE PDS LASSO, distance	267.613	54.512	0.029	0.328*	294.859
	(1148.211)	(377.577)	(0.205)	(0.195)	(938.663)
LATE PDS LASSO, traditional	2036.462	501.468	0.565	-0.423	-200.833
	(3355.757)	(1551.184)	(0.454)	(0.572)	(2175.385)
Difference	-1768.849	-446.956	-0.535	0.751	495.692
	(3519.602)	(1607.857)	(0.501)	(0.602)	(2428.380)
Control Means	2777.087	743.305	0.212	0.285	1574.522
Observations	276	276	276	276	276

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses. All specifications include stratum fixed effects and the de-meaned baseline outcome. Household income includes earnings from wages, salary, remittances, agriculture and livestock, non-farm businesses, and transfers. Women's total annual income calculated by adding up income from all sources where the woman in the sample was either the direct income recipient, the main laborer, or the main manager. Income control determined by asking which household members decide how to spend income generated by a given source.

Table 5: The Impact of Training on Savings by Training Type

	Deposits in personal savings in the past month	Deposits in household savings in the past month	Household total savings	Personal total savings
ITT, distance	-1.739	-18.022	288.536	9.594
	(5.758)	(41.218)	(403.558)	(149.710)
ITT, traditional	-4.343	-60.611	201.210	7.531
	(16.950)	(72.273)	(506.797)	(151.434)
Difference	2.604	42.589	87.326	2.063
	(17.901)	(83.200)	(647.844)	(212.944)
ITT PDS LASSO, distance	-1.739	-18.022	288.536	23.791
	(5.719)	(40.939)	(400.093)	(147.425)
ITT PDS LASSO, traditional	-4.343	-60.611	201.210	-5.433
	(16.835)	(71.783)	(502.444)	(129.131)
Difference	2.604	42.589	87.326	29.224
	(17.780)	(82.637)	(642.281)	(197.490)
LATE, distance	-3.529	-36.574	585.559	19.471
	(8.127)	(56.987)	(573.792)	(210.219)
LATE, traditional	-22.470	-313.596	1041.043	38.965
	(61.696)	(299.145)	(1873.905)	(544.433)
Difference	18.940	277.022	-455.485	-19.495
	(62.229)	(304.525)	(1959.785)	(583.609)
LATE PDS LASSO, distance	-3.529	-36.574	585.559	47.692
	(11.665)	(81.795)	(823.576)	(294.727)
LATE PDS LASSO, traditional	-22.470	-313.596	1041.043	-27.522
	(88.553)	(429.370)	(2689.658)	(666.011)
Difference	18.940	277.022	-455.485	75.213
	(89.318)	(437.092)	(2812.923)	(733.787)
Control mean	25.201	136.489	1505.248	434.109
Observations	276	276	276	276

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard are in parentheses. All specifications include stratum fixed effects and the de-meaned baseline outcome. All savings variables are in dollars.

Table 6: The impact of training on aspirations by training type

	Aspired people who would seek respondent's advice	Aspired income	Son aspiration index	Daughter aspiration index	Candidate aspiration index
ITT, distance	35.971	155.240	0.234	0.392	0.353*
	(32.725)	(303.696)	(0.181)	(0.270)	(0.192)
ITT, traditional	-83.773	-127.769	-0.147	-0.060	-0.283
	(51.035)	(1647.299)	(0.250)	(0.182)	(0.249)
Difference	119.744*	283.008	0.381	0.452	0.636**
	(60.626)	(1673.982)	(0.309)	(0.326)	(0.314)
ITT PDS LASSO, distance	33.001	155.240	0.234	0.392	0.353*
	(32.949)	(301.088)	(0.179)	(0.268)	(0.191)
ITT PDS LASSO, distance	-84.488*	-127.769	-0.147	-0.060	-0.283
	(49.356)	(1633.153)	(0.249)	(0.181)	(0.247)
Difference	117.489	283.008	0.381	0.452	0.636
	(59.304)	(1659.606)	(0.307)	(0.324)	(0.312)
LATE, distance	73.000	314.490	0.474*	0.795**	0.716**
	(48.737)	(423.736)	(0.259)	(0.405)	(0.296)
LATE, traditional	-433.435*	-622.429	-0.677	-0.313	-1.463
	(246.052)	(5687.692)	(0.857)	(0.688)	(1.117)
Difference	506.435	936.919	1.151	1.108	2.179
	(250.832)	(5697.321)	(0.896)	(0.798)	(1.156)
LATE PDS LASSO, distance	69.051	314.490	0.482**	0.788**	0.608***
	(70.595)	(609.382)	(0.197)	(0.308)	(0.197)
LATE PDS LASSO, traditional	-435.858	-622.429	-0.709	-0.289	-1.262*
	(352.170)	(8179.570)	(0.639)	(0.489)	(0.651)
Difference	504.909	936.919	1.191	1.077	1.870
	(360.479)	(8193.417)	(0.670)	(0.591)	(0.680)
Control mean	81.567	2676.861	0.051	-0.062	-0.030
Observations	276	276	274	276	276

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses. All specifications include stratum fixed effects. For aspired income, we also control for baseline aspired income. For aspired number of people who would seek the respondent's advice, we also control for baseline aspired number of women who would seek respondent's advice (number of men was not collected at baseline). Note that two households did not provide information on son aspirations.

is weak evidence that traditional training raised the probability of earning at least some non-farm income, with one of the two LATE estimates showing significance at the 10% level. None of the treatment effects are significantly different by training modality.

We estimate impacts on five indicators of aspirations: the aspired number of people who would ask the respondent for advice, aspired personal income level for the respondent, indices of aspirations for sons and daughters, and an overall index that combines all other outcomes. The indices combine outcomes into a weighted average where the largest weights are placed on outcomes with low variance and covariance with other outcomes (Anderson, 2008). Impacts on indices are measured in standard deviations. The son and daughter aspiration indices are built using responses to questions about aspired education level, aspired marriage age, and aspired occupation for the respondent's eldest son and daughter under the age of 16. If the respondent did not have a son/daughter, questions were asked about a hypothetical son or daughter.

Impacts on the overall respondent aspiration index suggest that distance learning raised aspirations. In particular, both LATEs are positive and precisely estimated. The positive LATEs appear to be driven by effects on the son and daughter aspiration indices. Child-level impacts (given in the appendix) show imprecise results, so it is difficult to attribute effects on the child aspiration indices to any particular outcome. Table 6 also shows weak evidence that traditional training may have lowered aspirations, particularly with respect to the number of people who would seek the respondent's advice.

5 Unpacking Results

5.1 Distance Learning and Constraints on Becoming a CAHW

Hybrid distance learning was clearly successful in boosting women's ability to become CAHWs, even among a group of women handpicked by their respective cooperatives. The question then becomes which constraints hybrid distance learning may have addressed. Possible constraints on completing training that could be addressed by hybrid distance learning include limitations on mobility and the inability to abandon household responsibilities, such as childcare. On the other hand, hybrid distance learning will not on its own improve acceptance of CAHWs, and a necessary condition for relaxation of constraints is sufficient comfort with the platform's technology.

In table 7, we present estimates of marginal effects from a logistic regression of training completion on assignment to distance learning, covariates, and interactions between distance learning and covariates.[1] Covariates were selected to represent different potential

[1]Using the PDS LASSO to select additional controls resulted in one more covariate being added to the

constraints: indices of comfort with technology, mobility, and empowerment;[2] indicators of responsibilities at home (the dependency ratio, an indicator for having an infant (under one year old) at baseline, household size, whether the household has a migrant); distance from the training center; and aptitude (education and livestock knowledge). The regression was estimated using the subsample assigned to CAHW training. We present marginal effects by assigned training modality as well as differences in marginal effects; the latter measure how the average treatment effect of being assigned to distance learning rather than traditional training changes as a given covariate is increased.

model and did not affect our results.

[2]The technology index is equal to the sum of indicators for using a Facebook account weekly and for regularly completing different tasks with a smartphone. The empowerment and mobility indices are inverse covariance-weighted sums of indicators computed just as was done for the aspirations index (Anderson, 2008). See the appendix for details.

Table 7: Marginal effects on completion of CAHW training

	Technology index	Mobility index	Empowerment index	Distance to training center	Dependency ratio (1-100)	Has an infant (0/1)	Household size	Household has a migrant (0/1)	Education (years)	Livestock knowledge score
Distance training	0.017	0.038**	-0.294***	-0.002**	0.002*	0.181	-0.065***	0.208*	0.033	0.007*
	(0.024)	(0.017)	(0.112)	(0.001)	(0.001)	(0.172)	(0.021)	(0.114)	(0.034)	(0.003)
Traditional training	-0.043	-0.015	-0.006	0.001	0.001	-0.249*	-0.002	-0.195*	0.031	0.004
	(0.027)	(0.026)	(0.059)	(0.001)	(0.002)	(0.129)	(0.016)	(0.106)	(0.031)	(0.002)
Difference	0.060*	0.052*	-0.288**	-0.003***	0.001	0.431**	-0.063**	0.403***	0.002	0.003
	(0.037)	(0.031)	(0.127)	(0.001)	(0.002)	(0.215)	(0.026)	(0.155)	(0.046)	(0.004)
Observations	139	139	139	139	139	139	139	139	139	139

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard errors in parentheses. The table shows marginal effects where having completed training is the dependent variable. The sample includes women assigned to training. Independent variables include an indicator for assignment to distance learning, the covariates shown in each column, and interactions between assignment to distance learning and the covariates. Marginal effects are computed at sample averages of the covariates.

Several results from table 7 are worth noting. First, it is expected that mobility would matter for completing training, but it is somewhat surprising that it only matters for distance learners. The difference in marginal effects indicates that a one standard deviation increase in the mobility index relative to the mean raises the impact of being assigned distance learning rather than traditional training by about 5 percentage points. One interpretation is that conditional on other variables we would expect to be associated with constraints, increasing freedom of mobility would be enough to make distance learning attainable for some women but not adequate for traditional training.

Whether we would expect mobility to be a binding constraint is unclear when examining baseline summary statistics. At baseline, the median number of times a respondent had been away from home overnight in the past year was six. 83% had not spent 30 days or more away from home in the past year, approximately the amount of time needed to complete traditional training.

Empowerment shows a pattern similar to that of mobility, as the former is negatively associated with training completion among distance learners and has no clear relationship with traditional training. Being more empowered strongly decreases the effect of being offered distance training rather than traditional training. We might expect higher empowerment to be associated with greater ease of acceptance of women as CAHWs within households, and would therefore have a positive effect on training completion. On the other hand, the empowerment index is a function of control over income, and women with greater access to income may have less interest in training. Still, it is unclear why this would only matter for distance learning.

If we want to look explicitly at the acceptance of female CAHWs dimension of empowerment, the relevant data were only collected at follow-up, in focus groups as well as in the follow-up survey. In focus groups, several respondents indicated that acceptance of female CAHWs in the community was a major impediment to success, and that practicing castration (a normal practice for CAHWs) was seen as shameful for women. In contrast, the survey data suggest that households were very accepting of female CAHWs. Since acceptance may have been impacted by treatment, we must use the control group to shed light on this issue.[3] Nearly all women in the control group, as well as male and female relatives selected for interviews (usually the husband or mother-in-law, respectively), agreed that women could manage livestock just as well as men and be just as effective as CAHWs. Male and female CAHWs were viewed as equally capable even with respect to castration. In contrast, about 20% of women in the study as well as their relatives indicated that women could not handle large livestock as well as men. But on the whole, these data suggest that screening of potential candidates largely removed acceptance of female CAHWs as a constraint, at least within households.

Although the marginal effects of the technology index are imprecisely estimated for each training type, the difference in marginal effects is statistically significant. The difference in marginal effects indicates that a one standard deviation increase (1.92) in the index relative to the mean (3.24) would raise the impact on completing training of being offered distance learning rather than traditional training by 11.5 percentage points.

Distance from the nearest training center does not seem to matter much for training completion. Although the marginal effect for women assigned to distance learning is significant, as is the difference in marginal effects, the magnitude of the differences suggests that moving from 100 kilometers away (the sample average) to 50 kilometers away would increase the probability of completing distance training by 1.5 percentage points.

Having an infant (a child one year old or younger) at baseline is a strong predictor of training completion for women assigned to traditional training, as well as an important dimension of treatment effect heterogeneity for training completion. As compared to women without an infant at baseline, the impact of being offered distance learning rather than traditional training is 43 percentage points larger for women with an infant. As noted earlier, training centers do not have childcare. It is no surprise that a potentially nursing

[3] There are no impacts on CAHW acceptance but it still seems proper to assess acceptance in the absence of treatment using the control group.

mother would find it difficult to complete traditional training. At baseline, 12% of women assigned to training had an infant. The dependency ratio, which is based on the number of children younger than 14 and the number of adults 65 and older relative to household size as whole, has a weak effect on completing distance training but no discernible impact otherwise.

Household size reduces the probability of completing distance training as well as the effect of being offered distance learning rather than traditional training, a result that makes sense if larger households imply more distractions. Having a migrant has large and contrasting effects on completing the two forms of training. The difference in marginal effects is significant, and implies that the effect of being offered distance learning rather than traditional training is 39 percentage points larger for women in households with a migrant than those without. Some focus group respondents indicated that sending a migrant can increase responsibilities at home, and that only with hybrid distance learning was it possible to complete training. The results in table 7 support this conclusion.

5.2 Impacts on Aspirations

Table 6 suggests that the aspired number of women who would seek the respondent out for advice fell as a result of traditional training. In follow-up phone conversations, traditional trainees could not point to any negative experiences that might have driven observed effects on aspirations. But it could be the case that traditional trainees had high expectations for their new jobs and were disappointed by their experiences once they began working. This could have had a discouraging effect, lowering aspirations.

5.3 The Absence of Impacts on Income or Savings

Although there is evidence to suggest distance learning increased women's control over income (see table 4), training had no discernible effect on average income. One potential

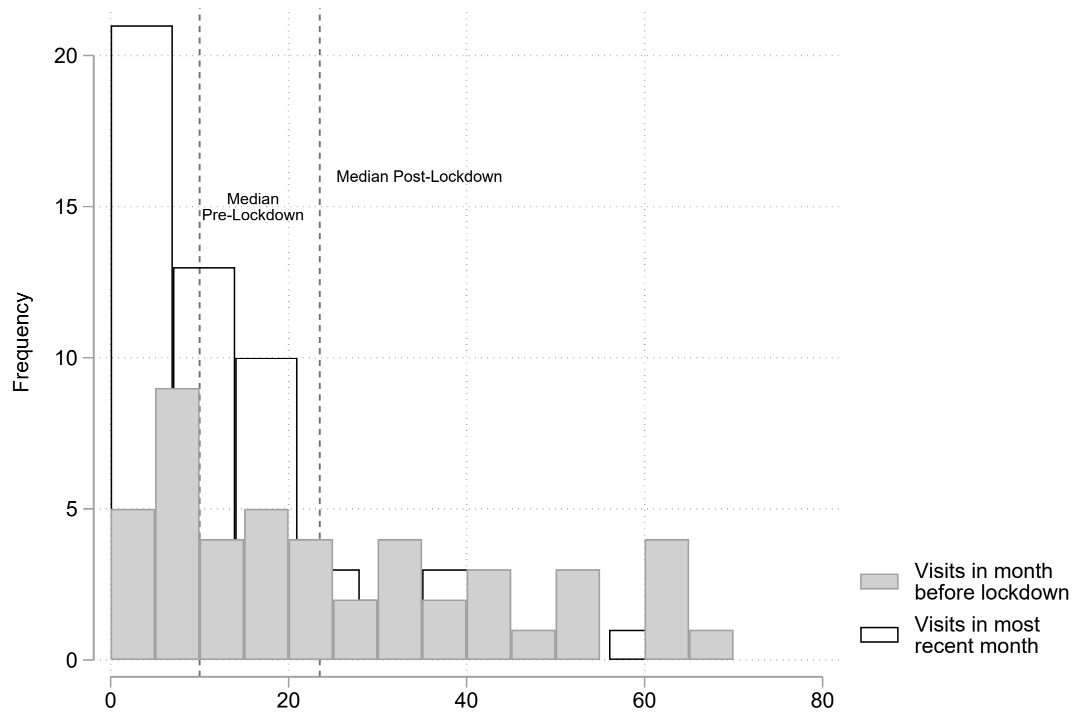

Figure 2: Visits to Clients, Pre and Post-Lockdown

explanation is restrictions on mobility instituted by the Government of Nepal in response to Covid-19, or just the general economic malaise caused by the pandemic. Figure 2 shows the distribution of client visits for women assigned to CAHW training, one month prior to the follow-up interview and one month immediately before lockdown began; outliers above 90 visits per month were trimmed. The median number of client visits in the past month is ten. The same sample of women reported a median number of visits of 23.5 in the month prior to lockdown. Prior to lockdown, 54 of 60 women were averaging at least one client visit per week. In the month prior to the follow-up interview, 43 of 60 were averaging at least one per week. Follow-up data were collected in January 2021 while lockdown began in March of 2020, so part of the gap could be explained by recall error. But lockdown was a very salient event. It could also be the case that women are gradually exiting the profession, and that this would have happened regardless of lockdown. But figure 2 suggests that CAHW income may have fallen because of an inability to visit clients.

The absence of effects on average income does not rule out distributional effects. In table 8, we estimate quantile effects of being assigned to distance learning, while table 9 reports instrumental variable estimates of the quantile effects of completing training (Chernozhukov and Hansen, 2005). Both sets of estimates represent treatment effects under the assumption of rank invariance. For the effect of being assigned to treatment, rank invariance implies that if everyone were given the same treatment assignment, individual rankings in the outcome distribution would stay the same regardless of which treatment status was assigned to everyone. For the instrumental variables estimates, rank invariance is assumed with respect to treatment status rather than assignment. If rank invariance does not hold, then the results in tables 8 and 9 measure shifts in quantiles without capturing treatment effects on specific individuals.

The results in table 8 suggest that assignment to distance training boosted control over income for women below the median of the distribution for jointly controlled income. There is weaker evidence that household income and income earned by the respondent were shifted because of treatment assignment. The instrumental variables estimates show a similar pattern, with effects on jointly-controlled income showing statistical significance at the 15%, 25%, and 35% quantiles. The instrumental variables estimates are less precise than those in table 8, and none of the differences in effects by training modality are significant.[4]

5.4 Disentangling the Role of Training Modality and Trainee Characteristics

Differences in ITTs by training system can be driven by rates of participation in training, the characteristics of individuals selecting into each training type (i.e., endogenous selection into treatment), and the relative effectiveness of each training system. The LATEs remove any difference in treatment effects explained by rates of participation in treatment, but can still be driven by a mixture of endogenous selection and training effectiveness. LATEs capture

[4]Note that we do not examine solely-controlled income because most of the quantiles are zero. Also, quantile regressions for savings outcomes showed no effects.

effects on compliers, i.e., those who would participate in training if invited to do so and not otherwise, and there may be limited overlap between the complier populations for the two training systems. Therefore endogenous selection may play a role in explaining LATEs for each training system.

To isolate the role of training system effectiveness in explaining differences in treatment effects by modality, we impute average outcomes that would have been obtained by traditionally-trained CAHWs had they completed hybrid distance training. We then test for differences in observed average outcomes among traditionally-trained CAHWs and their imputed average outcomes under distance training. We use three imputation methods. First, we compare average outcomes among the two types of CAHWs. Second, we estimate a linear regression model using the subsample of distance-trained CAHWs, and estimate the average outcome while holding covariate values at their averages in the sample of traditionally-trained CAHWs:

$$\bar{\bar{y}}_{DL} = \bar{X}_{TT}' \hat{\beta}_{DL} \tag{4}$$

where $\bar{\bar{y}}_{DL}$ is the imputed distance-learning mean for traditionally-trained CAHWs, $\bar{X}_{TT}$ is a vector of sample averages among traditionally-trained CAHWs, and $\hat{\beta}_{DL}$ is a vector of coefficients estimated using the subsample of distance-trained CAHWs. We choose the covariate vector using the LASSO algorithm applied to the subsample of distance-trained CAHWs, using the same pool of covariates from our main LASSO results above as well as significant predictors from table 7 (distance to the nearest training center, a technology index based on social media and smartphone use, and an indicator for having an infantl; having a migrant was already included in the main set of covariates).

Our third approach is to use a Heckman sample-selection model (Heckman, 1976). First, we estimate a probit model of selection into distance training, using the sample of women in cooperatives assigned to distance training:

$$P\left(CAHW_i^{DL}|Z_i\right) = \Phi\left(Z_i'\delta\right) \tag{5}$$

where $P\left(CAHW_i^{DL}|X_i, INV_i\right)$ represents the probability of becoming a distance-trained CAHW conditional on a vector of predictors Z_i, $\Phi\left(\ \right)$ is the standard normal cumulative density function, and δ is a vector of coefficients to be estimated. The vector Z_i includes covariates (X_i) as well as an indicator for random assignment to distance training (INV_i). From the results of the probit equation, we obtain the inverse mills ratio, i.e., $\hat{\lambda}_i = \phi\left(Z_i'\hat{\delta}\right)/\Phi\left(Z_i'\hat{\delta}\right)$, where $\phi\left(Z_i'\hat{\delta}\right)$ represents the standard normal probability distribution function. To identify the inverse mills ratio among traditionally-trained CAHWs, we have to assume that anyone completing traditional training would have also completed distance training if given the chance. We then estimate a linear regression model of y_i using our subsample of distance-trained CAHWs, where the model's right-hand side includes the covariate vector used in equation 4 as well as the inverse mills ratio. We impute the distance-trained mean outcome for traditionally trained CAHWs as:

$$\bar{\hat{y}}_{DL} = \bar{X}_{TT}'\hat{\beta}_{DL} + \hat{\gamma}_{DL}\bar{\hat{\lambda}}_{TT} \tag{6}$$

The Heckman approach is unbiased for the imputed mean if the error term in the population regression $y_{i,DL} = X_i'\beta + u_i$ and the error term from the probit model given by equation 5 are jointly normal, with covariance given by the population analog to $\hat{\gamma}_{DL}$. Admittedly, the assumption of normality is unlikely to hold. Therefore we view the Heckman approach as providing a robustness check on our linear regression imputation models, i.e., checking whether regression results hold after adjusting for unobserved selection. The parameter estimates for equations 5 and 6 are obtained by maximum likelihood.

Our outcomes of interest include the knowledge and livestock management indicators shown in table 3 and a collection of outcomes only observed among CAHWs: number of client visits in the past month and in a typical month before lockdown, indicators of services provided to clients (to assess competency), and binary indicators for earning at least some CAHW income and investing in the CAHW business. We use binary indictors of income and investment because the means of the continuous variables were dominated by outliers even after top coding. We combine all outcomes into a single index, just as we did for aspirations in table 6. Results are given in table 10.

For eight of 18 outcomes, the LASSO algorithm retains predictors in the model, while in the remainder no predictors survive shrinkage, likely because of the small sample size; in the latter case, the unadjusted and adjusted means are the same. Our results suggest that traditionally-trained CAHWs would have performed better along several dimensions had they completed distance training. Specifically, traditionally-trained CAHWs would complete more livestock management tasks at home, would have had more clients in the previous month, and would have provided more services to their clients. These conclusions are tempered by the fact that the performance index shows no impacts.

Since $\bar{X}'_{TT}\hat{\beta}_{DL}$ is also an estimate of the mean outcome distance-trained CAHWs would have obtained if they had the same characteristics as traditionally-trained CAHWs, we can use the results in table 10 to check for evidence of endogenous selection into training. Our results suggest that, if anything, trainees of lower quality selected into distance learning. The first column in table 10 is equal to $\bar{y}_{TT} - \bar{y}_{DL}$ while the second column is equal to $\bar{y}_{TT} - \bar{X}'_{TT}\hat{\beta}_{DL}$ (where the second term includes the inverse mills ratio in column 3). Therefore anytime the first column is greater than columns two and three, we have evidence of negative selection into distance training. That is, $\bar{y}_{DL} < \bar{X}'_{TT}\hat{\beta}_{DL}$, so that distance-trained CAHWs would have better average outcomes with traditionally-trained CAHW characteristics. For all of our significant results in table 10, the first column is greater than columns two and three, indicating negative selection into distance training.

Table 8: Quantile Effects of Assignment to Treatment on Income

	Total household income	Respondent income	Jointly controlled income
Quantile = 15%, distance	562.957*	72.000	0.720
	(299.177)	(75.541)	(212.063)
Quantile = 15%, traditional	181.588	40.702	0.000
	(267.144)	(57.242)	(181.448)
Difference	381.369	31.298	0.720
	(341.438)	(78.546)	(247.610)
Quantile = 25%, distance	541.595*	118.000*	500.441**
	(306.985)	(70.167)	(200.342)
Quantile = 25%, traditional	416.399	34.318	0.000
	(344.212)	(66.138)	(153.045)
Difference	125.196	83.682	500.441**
	(390.996)	(86.807)	(207.725)
Quantile = 35%, distance	463.811	145.164*	620.000***
	(310.633)	(85.701)	(232.785)
Quantile = 35%, traditional	98.526	44.587	-80.000
	(382.103)	(74.064)	(164.124)
Difference	365.285	100.578	700.000***
	(407.717)	(108.073)	(249.044)
Quantile = 50%, distance	317.800	227.143	345.627
	(475.204)	(148.234)	(277.573)
Quantile = 50%, traditional	273.300	57.143	-215.932
	(422.417)	(128.762)	(213.705)
Difference	44.500	170.000	561.559
	(560.490)	(174.698)	(346.586)
Quantile = 75%, distance	317.800	-71.000	71.208
	(475.204)	(202.174)	(468.394)
Quantile = 75%, traditional	273.300	131.429	278.196
	(422.417)	(521.800)	(350.940)
Difference	44.500	-202.429	-206.989
	(560.490)	(526.847)	(478.398)
Observations	276	276	276

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses (Parente and Silva, 2016). All regressions include lagged outcomes.

Table 9: Instrumental Variables Estimates of Quantile Effects on Income

	Total household income	Respondent income	Jointly controlled income
Quantile = 15%, distance	950.990**	190.743	503.503
	(391.404)	(141.207)	(350.103)
Quantile = 15%, traditional	1157.015	119.741	-342.120
	(1186.232)	(223.552)	(1182.030)
Difference	-206.025	71.002	845.622
	(1089.416)	(227.281)	(1091.606)
Quantile = 25%, distance	1044.834**	249.707	707.937*
	(503.371)	(178.349)	(410.430)
Quantile = 25%, traditional	1421.577	130.181	-544.511
	(1766.434)	(10073.318)	(5.972e+06)
Difference	-376.744	119.527	1252.448
	(1618.332)	(10055.999)	(5.972e+06)
Quantile = 35%, distance	897.678	403.965**	846.570*
	(755.737)	(201.353)	(445.779)
Quantile = 35%, traditional	983.588	176.733	-687.975
	(5627.764)	(601.238)	(1318.112)
Difference	-85.910	227.232	1534.545
	(5471.302)	(595.091)	(1203.981)
Quantile = 50%, distance	895.935	497.886	793.923
	(1080.844)	(317.855)	(889.164)
Quantile = 50%, traditional	1084.524	190.956	-781.548
	(2720.225)	(855.505)	(1805.334)
Difference	-188.589	306.930	1575.471
	(2609.175)	(866.116)	(1658.538)
Quantile = 75%, distance	1622.242	-113.679	554.022
	(1534.676)	(439.260)	(1370.130)
Quantile = 75%, traditional	1315.554	251.853	760.428
	(2539.587)	(2135.778)	(1772.745)
Difference	306.688	-365.532	-206.406
	(2499.160)	(2048.299)	(1989.876)
Observations	276	276	276

Notes: * p <0.10, ** p <0.05, *** p <0.01. Bootstrap cluster-robust standard are in parentheses. All regressions include lagged outcomes.

Table 10: Comparing outcomes with traditional and distance training, traditional trainees

	Mean with traditional training - Mean with distance training		
	Unadjusted	Regression	Sample selection
CAHW performance index	0.0820	0.0820	0.197
	(0.204)	(0.202)	(0.225)
Percentage of easy questions correct	0.260	0.260	0.0943
	(1.892)	(1.876)	(1.799)
Percentage of intermediate questions correct	8.064	-12.80	-13.89
	(8.214)	(7.891)	(9.027)
Percentage of difficult questions correct	-0.669	-0.669	-1.183
	(3.277)	(3.250)	(3.124)
Overall knowledge score	-0.495	-4.072	-4.539
	(3.043)	(3.551)	(3.427)
Livestock management easy tasks, at home	0.0970	-1.016**	-1.174**
	(0.438)	(0.501)	(0.578)
Livestock management difficult tasks, at home	-0.0167	-1.041*	-1.350**
	(0.470)	(0.539)	(0.531)
Client visits in month before lockdown (inverse hyperbolic)	-0.0699	0.0182	0.0116
	(0.402)	(0.370)	(0.409)
Client visits in past month (inverse hyperbolic)	0.123	-0.760**	-0.598*
	(0.339)	(0.347)	(0.352)
Percent of easy services performed in past year	-0.0156	-0.0156	0.0145
	(0.0575)	(0.0571)	(0.0582)
Percent of easy services successfully provided	-0.877	-0.877	1.612
	(5.605)	(5.557)	(5.804)
Percent of easy services independently provided	-2.432	-13.36*	-16.05**
	(6.189)	(6.834)	(7.083)
Percent of hard services performed in past year	0.0355	0.0355	0.0626
	(0.0561)	(0.0556)	(0.0718)
Percent of hard services successfully provided	3.628	3.628	5.816
	(5.654)	(5.606)	(7.001)
Percent of hard services independently provided	4.426	-7.660	-6.723
	(5.287)	(5.361)	(6.278)
CAHW income (0/1)	-0.0803	-0.0803	-0.0962
	(0.129)	(0.128)	(0.140)
Invested in CAHW business (0/1)	0.0412	0.0412	0.102
	(0.0867)	(0.0860)	(0.113)
Used seed money for CAHW business (0/1)	-0.0201	-0.0201	0.0401
	(0.106)	(0.105)	(0.133)
Observations	62	62	166

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses. The mean outcome with distance training is imputed in the first column with the sample average among distance-trained CAHWs, in the second column by OLS with distance-trained CAHWs, and in the third column using a Heckman sample selection model with women assigned to distance training. For each outcome, covariates were selected using a LASSO model of the outcome, where the LASSO tuning parameter was chosen by five-fold cross-validation. LASSO covariates include all the same predictors used for our main models (see the appendix) as well as distance to the nearest training center, a technology index based on social media and smartphone use, and an indicator for having an infant (all measured at baseline).

6 Conclusion

We evaluated the effects of hybrid distance learning and traditional classroom-based training for CAHWs on training completion, livestock knowledge and management, income, savings, and aspirations. Neither type of training affected average income. We find weak evidence that distance learning increased the proportion of women controlling at least some income. Quantile regressions support the conclusion that training boosted income control, showing positive impacts for amount of income jointly controlled by women at quantiles below the median. Neither intervention had any effect on savings. Indicators of livestock knowledge and management were significantly increased by distance training, with impacts on easy management practices implemented by women at home significantly higher for distance learners. We find suggestive evidence that distance learning was the superior training modality, and that relatively low-quality trainees selected into distance training. These last results are tempered by the fact that an overall index of CAHW performance showed no differences by training modality.

The hybrid distance learning system was designed with the belief that making training available on tablets would relax specific constraints on women's participation in entrepreneurial activities, in particular, restrictions on mobility arising from gender norms or time-consuming responsibilities at home. We tested several mechanisms that might explain why distance learning was so effective in boosting training completion relative to traditional training. Being offered distance learning was especially effective for women with greater freedom of mobility, women with an infant, women from smaller households, and women from households with at least one migrant.

As with any study, our has limitations. First, since training women for jobs that did not exist would have been unethical, and we could not ask the cooperatives to pick training candidates purely at random (to give us a larger control group), we were forced to use a fairly small sample. Our sample size limits our study in two ways. First, we lack power to detect small treatment effects or differences in treatment effects by training modality.

Second, we were unable to introduce additional treatment arms that would have held some of the differences between hybrid distance learning and traditional training fixed, e.g., have women study in training centers with tablets, or vary length of the study period.

Regardless of limitations, we view our study as providing strong evidence that hybrid distance learning can produce skilled rural service providers and open the door to rural women becoming entrepreneurs. Weak evidence for hybrid distance learning allowing lower-quality candidates to complete training appears to be outweighed by strong evidence for distance learning expanding women's entrepreneurial opportunities. If the goal is to expand the supply of animal health professionals in rural communities while boosting employment opportunities for rural women, hybrid distance learning appears to be a success. If the goal is to expand the supply of animal health professionals while keeping the quality of service providers fixed, then more research may be needed to measure the net impact of endogenous selection into hybrid distance training and the effectiveness of the training platform itself. Other issues of interest include identifying the optimal monitoring program for distance trainees, testing whether hybrid distance learning is more effective for women than men (because of different constraints on completing training), and exploring whether mobile technology can be used for more sophisticated training once rural women earn initial certification to work as CAHWs (or any other profession). These questions could be the subject of future research.

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A Appendix

A.1 Deviations from Pre-Analysis Plan

In our pre-analysis plan, we did not specify that we would estimate and compare the impacts of aspirations by training type. We also did not specify that we would replace some income indicators with binary variables. This choice was made after seeing that income control variables had relatively few non-zero values, with extremely large outliers remaining even after top-coding. The supplementary analyses found in the main text under "Unpacking Results" were not pre-specified. We did specify that we would try to disentangle endogenous selection from the effects of the training modalities, and we did say we might use a Heckman model as well as a selection-on-observables approach. In the pre-analysis plan we said we would use another round of survey data in our analysis. Distance-trained and traditionally-trained CAHWs received additional training from Heifer before we could collect endline data, likely erasing differences arising from assigned training system. Therefore endline data are not featured in our analysis.

A.2 Child-Level Impacts on Aspirations

In tables A.1 and A.2, we present child-level impacts on indicators of aspirations. Note that the indices in the main text were built by using data on the oldest child, whereas the results below are for all children. For households that did not have a son/daughter, we asked questions about a hypothetical son/daughter.

Table A.1: The impact of training on aspirations for sons, by training type

	Aspired son's education	Aspired son's marriage age	Aspired son's occupation is tier 1 or 2 (0/1)	Aspired son's occupation is tier 1 (0/1)	Son aspiration index
ITT, distance	0.339	0.775	-0.037	-0.024	0.287
	(0.490)	(0.589)	(0.076)	(0.023)	(0.203)
ITT, traditional	-0.243	-0.465	0.092	-0.005	-0.198
	(0.649)	(0.611)	(0.081)	(0.037)	(0.258)
Difference	0.582	1.239	-0.129	-0.019	0.485
	(0.813)	(0.849)	(0.111)	(0.044)	(0.329)
ITT PDS LASSO, distance	0.339	0.775	-0.037	-0.024	0.287
	(0.487)	(0.585)	(0.075)	(0.023)	(0.202)
ITT PDS LASSO, traditional	-0.243	-0.465	0.092	-0.005	-0.198
	(0.644)	(0.607)	(0.081)	(0.037)	(0.257)
Difference	0.582	1.239	-0.129	-0.019	0.485
	(0.807)	(0.843)	(0.110)	(0.043)	(0.326)
LATE, distance	0.674	1.541*	-0.073	-0.048	0.572*
	(0.693)	(0.934)	(0.111)	(0.034)	(0.304)
LATE, traditional	-1.098	-2.098	0.415	-0.024	-0.893
	(2.248)	(2.136)	(0.292)	(0.122)	(0.932)
Difference	1.772	3.639	-0.488	-0.023	1.465
	(2.353)	(2.331)	(0.312)	(0.127)	(0.980)
LATE PDS LASSO, distance	0.674	1.541	-0.073	-0.048	0.572
	(0.943)	(1.270)	(0.151)	(0.047)	(0.413)
LATE PDS LASSO, traditional	-1.098	-2.098	0.415	-0.024	-0.893
	(3.057)	(2.905)	(0.397)	(0.166)	(1.267)
Difference	1.772	3.639	-0.488	-0.023	1.465
	(3.199)	(3.170)	(0.425)	(0.173)	(1.333)
Control mean	17.692	26.103	0.128	0.026	-0.033
Observations	309	309	309	309	309

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses. All specifications include stratum fixed effects. The sample size differs from the number shown in the aspirations results from the main text because the estimates presented here are at the child level.

A.3 Spillovers Analysis

We check for robustness to spillovers for the two domains where they are most likely to be found: knowledge and income. We add three sets of variables to our main regression

Table A.2: The impact of training on aspirations for daughters, by training type

	Aspired daughter's education	Aspired daughter's marraige age	Aspired daughter's occupation is tier 1 or 2 (0/1)	Aspired daughter's occupation is tier 1 (0/1)	Daughter aspiration index
ITT, distance	0.375	0.560	-0.089	-0.032	0.439
	(0.526)	(0.505)	(0.072)	(0.031)	(0.282)
ITT, traditional	0.027	-0.316	-0.003	0.000	-0.051
	(0.697)	(0.451)	(0.085)	(0.000)	(0.182)
Difference	0.348	0.877	-0.086	-0.032	0.490
	(0.874)	(0.677)	(0.112)	(0.031)	(0.335)
ITT PDS LASSO, distance	0.375	0.560	-0.089	-0.032	0.439
	(0.523)	(0.502)	(0.072)	(0.031)	(0.280)
ITT PDS LASSO, traditional	0.027	-0.333	-0.003	-0.000	-0.051
	(0.693)	(0.447)	(0.085)	(0.000)	(0.181)
Difference	0.348	0.893	-0.086	-0.032	0.490
	(0.868)	(0.672)	(0.111)	(0.031)	(0.333)
LATE, distance	0.740	1.106	-0.175	-0.063	0.867**
	(0.750)	(0.725)	(0.108)	(0.045)	(0.420)
LATE, traditional	0.137	-1.616	-0.014	-0.000	-0.261
	(2.543)	(1.677)	(0.311)	(0.000)	(0.700)
Difference	0.603	2.723	-0.161	-0.063	1.127
	(2.651)	(1.827)	(0.329)	(0.045)	(0.816)
LATE PDS LASSO, distance	0.740	1.106	-0.175	-0.063	0.867
	(1.038)	(1.004)	(0.149)	(0.063)	(0.582)
LATE PDS LASSO, traditional	0.137	-1.658	-0.014	-0.000	-0.261
	(3.520)	(2.266)	(0.431)	(0.000)	(0.968)
Difference	0.603	2.764	-0.161	-0.063	1.127
	(3.670)	(2.478)	(0.456)	(0.063)	(1.129)
Control mean	17.527	24.284	0.162	0.014	-0.092
Observations	297	297	297	297	297

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses. All specifications include stratum fixed effects. The sample size differs from the number shown in the aspirations results from the main text because the estimates presented here are at the child level.

specification to check for spillovers: the count of women in the sample within a given distance of the respondent, the count of women assigned to training within a given distance, and the interaction between the two treatment dummies and the count of women assigned to treatment within a given distance. The distances we use are within one kilometer, between one and five kilometers, and between five and ten kilometers. In total we add 12 variables to our main regression specification. Results are given in tables A.3 and A.4. We only report the coefficients on the counts of women assigned to training since those are coefficients that measure spillovers onto the control group, and could therefore bias our estimates. Knowledge impacts become less precise when controlling for spillovers but do not change very much relative to sampling uncertainty. It is unsurprising that estimated ITTs would become less precise after adding a large number of variables with little explanatory power to the model. For income, the estimated impact on the indicator for solely controlling at least some income becomes larger and more precise, but our results are hardly changed otherwise.

Table A.3: Livestock knowledge and management, controlling for spillovers

	Percent correct, easy livestock questions	Percent correct, intermediate livestock questions	Percent correct, hard livestock questions	Overall score	Number of easy health practices, own livestock	Number of hard health practices, own livestock
ITT, distance	5.320	19.960	3.772	0.088	1.005*	0.823
	(8.161)	(18.538)	(6.568)	(0.080)	(0.595)	(0.564)
ITT, traditional	2.077	7.594	2.774	0.031	-0.382	0.008
	(7.713)	(17.058)	(5.808)	(0.072)	(0.594)	(0.516)
Trainees, 1 km	-3.474	-1.091	-2.110	-0.038	-0.356	-0.268
	(9.100)	(16.713)	(6.215)	(0.078)	(0.649)	(0.571)
Trainees, 1-5 km	-11.274	-8.012	-5.456	-0.084	0.292	0.137
	(11.998)	(24.707)	(9.764)	(0.131)	(0.984)	(0.920)
Trainees, 5-10 km	1.918	-4.796	-6.433	-0.006	-0.038	-0.277
	(7.469)	(13.927)	(5.831)	(0.065)	(0.689)	(0.645)
Difference	3.244	12.366	0.998	0.057	1.386***	0.815
	(6.267)	(13.209)	(6.271)	(0.062)	(0.511)	(0.556)
ITT PDS LASSO, distance	5.404	20.097	3.961	0.089	1.011*	0.821
	(7.936)	(17.988)	(6.414)	(0.078)	(0.578)	(0.548)
ITT PDS LASSO, traditional	2.061	7.652	2.790	0.030	-0.385	0.009
	(7.492)	(16.518)	(5.618)	(0.069)	(0.577)	(0.501)
Trainees, 1 km	-3.377	-0.945	-1.901	-0.037	-0.347	-0.270
	(8.845)	(16.222)	(6.069)	(0.076)	(0.631)	(0.556)
Trainees, 1-5 km	-11.043	-7.727	-5.031	-0.081	0.321	0.131
	(11.681)	(24.055)	(9.499)	(0.127)	(0.959)	(0.898)
Trainees, 5-10 km	1.890	-4.770	-6.442	-0.006	-0.043	-0.276
	(7.269)	(13.522)	(5.732)	(0.064)	(0.676)	(0.624)
Difference	3.343	12.445	1.171	0.058	1.396***	0.812
	(6.098)	(12.799)	(6.062)	(0.060)	(0.498)	(0.543)
Control mean	87.348	60.097	52.068	0.659	1.715	0.993
Observations	276	276	276	276	276	276

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses. All specifications include stratum fixed effects, de-meaned baseline outcome, interactions between treatment dummies and the trainee distance count variables shown in the table, and counts of the total sample members within the three distances shown in the table.

A.4 Power Analysis

In table A.5 we present minimum detectable effects (MDEs) for our intent-to-treat estimators. Using standard rules of thumb (Cohen, 1988), most MDEs for the effects of distance learning and traditional training approximately qualify as indicating adequate power for medium sized effects (i.e., around 0.50 standard deviations). MDEs for the difference in intent-to-treat effects are larger. When examining the MDEs in the original units of each

Table A.4: Income impacts, controlling for spillovers

	Total household annual income	Woman's total annual income	Woman's non-farm annual income (0/1)	Woman's annual solely controlled income (0/1)	Woman's annual jointly controlled income
ITT, distance	-477.222	34.401	0.206	0.443**	-398.753
	(1237.597)	(559.739)	(0.256)	(0.213)	(856.120)
ITT, traditional	-143.786	-81.201	0.271	0.255	-521.490
	(1216.259)	(587.042)	(0.195)	(0.189)	(834.310)
Trainees, 1 km	-782.486	-193.670	0.128	0.351*	-454.594
	(1212.609)	(568.428)	(0.236)	(0.197)	(836.022)
Trainees, 1-5 km	344.219	125.555	0.341	0.292	-222.197
	(1398.114)	(596.361)	(0.292)	(0.349)	(973.513)
Trainees, 5-10 km	-803.586	-185.156	0.204	0.291	-1250.794
	(1345.671)	(659.354)	(0.232)	(0.226)	(865.830)
Difference	-333.436	115.601	-0.065	0.188	122.737
	(1000.128)	(396.909)	(0.146)	(0.174)	(706.713)
ITT PDS LASSO, distance	-477.222	25.867	0.208	0.447**	-396.812
	(1197.399)	(546.830)	(0.249)	(0.206)	(831.887)
ITT PDS LASSO, traditional	-143.786	-76.884	0.270	0.254	-521.919
	(1176.754)	(581.173)	(0.191)	(0.183)	(809.867)
Trainees, 1 km	-782.486	-205.596	0.131	0.356*	-452.269
	(1173.223)	(557.583)	(0.230)	(0.190)	(812.632)
Trainees, 1-5 km	344.219	86.790	0.350	0.306	-215.328
	(1352.702)	(578.886)	(0.285)	(0.338)	(948.050)
Trainees, 5-10 km	-803.586	-177.811	0.202	0.289	-1250.978
	(1301.963)	(641.976)	(0.225)	(0.219)	(839.163)
Difference	-333.436	102.751	-0.062	0.192	125.106
	(967.643)	(383.900)	(0.139)	(0.167)	(687.117)
Control Means	2777.087	743.305	0.212	0.285	1574.522
Observations	276	276	276	276	276

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses. All specifications include stratum fixed effects, de-meaned baseline outcome, interactions between treatment dummies and the trainee distance count variables shown in the table, and counts of the total sample members within the three distances shown in the table.

outcome, the situation appears a bit better. In particular, MDEs for completing training, knowledge questions, and number of management tasks all appear quite reasonable. Continuous income variables have large MDEs by any measure, while the binary measures are more realistic, particularly for earning at least some non-farm income. Savings outcomes also have large MDEs by any reasonable standard, as does aspired income. It is difficult to say what constitutes a reasonable MDE for other indicators of aspirations.

Table A.5: Minimum Detectable Effects, Intent-to-Treat

	Minimum detectable effects, original units			Minimum detectable effects, standard deviations		
	ITT, distance	ITT, traditional	ITT, difference	ITT, distance	ITT, traditional	ITT, difference
Completed training (0/1)	0.264	0.284	0.388	1.286	1.384	1.889
Easy questions (percent)	13.416	11.753	17.731	0.615	0.539	0.813
Intermediate questions (percent)	22.624	24.415	33.326	0.549	0.593	0.809
Hard questions (percent)	11.013	11.103	15.778	0.570	0.574	0.816
Total score (percent)	12.430	9.856	15.787	0.593	0.471	0.754
Easy tasks (count)	1.053	1.035	1.477	0.707	0.695	0.991
Hard tasks (count)	0.977	1.047	1.432	0.820	0.879	1.202
Household income	1627.347	1881.298	2486.333	0.704	0.813	1.075
Respondent income	528.707	886.002	1038.841	0.550	0.921	1.080
Respondent non-farm income (0/1)	0.304	0.222	0.376	0.742	0.541	0.918
Solely controls some income (0/1)	0.277	0.359	0.456	0.612	0.792	1.006
Jointly-controlled income	1300.615	1167.430	1783.817	0.743	0.667	1.019
Personal savings past month	16.131	47.487	50.152	0.301	0.885	0.935
Household savings past month	115.476	202.478	233.092	0.385	0.675	0.777
Household total savings	1130.603	1419.834	1814.991	0.627	0.787	1.007
Personal total savings	419.424	424.254	596.581	0.667	0.675	0.949
Aspired number seeking advice (count)	92.486	144.373	172.737	0.506	0.790	0.946
Aspired income	850.831	4615.049	4689.803	0.164	0.890	0.904
Boy aspirations index	0.506	0.701	0.865	0.525	0.727	0.897
Girl aspirations index	0.756	0.511	0.913	0.642	0.434	0.775
Aspirations index	0.538	0.697	0.880	0.470	0.610	0.770

Notes: * p <0.10, ** p <0.05, *** p <0.01. Cluster-robust standard are in parentheses. All specifications used to estimate the minimum detectable effects include stratum fixed effects and the de-meaned baseline outcome when available. Minimum detectable effects in standard deviations use the standard deviation of the outcome for the control group.