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Delivery Mechanisms and Impact of Training through Microfinance

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DELIVERY MECHANISMS AND IMPACT OF TRAINING THROUGH MICROFINANCE

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Delivery Mechanisms and Impact of Training through Microfinance

Ranjula Bali Swain* and Adel Varghese♦

Abstract

We evaluate the effect of delivery mechanisms for training provided by facilitators of self help groups (SHGs). Indian SHGs are unique in that they are mainly NGO-formed microfinance groups but later funded by commercial banks. We correct for both membership and training endogeneity. Training impacts assets but not income. Underlying conditions that benefit training include better infrastructure (as in paved roads), linkage model type, and training organizer.

Keywords – Asia, India, microfinance, impact studies, training, Self Help Groups

JEL: G21, I32, O12.

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1. Introduction

In a recent impact and sustainability study of the Self Help Group (SHG) Bank Linkage Program, NCAER (2008) finds that SHGs have significantly improved the access to financial services of the rural poor. The report also finds a considerable positive impact for the socio-economic conditions of SHG members. In addition to financial services, SHGs also provide both skill development and human capital training services to their members.

This paper aims to explore the impact of the delivery of these training mechanisms. In complementary work, Bali Swain and Varghese (2010) find that training positively impacts assets but not income.¹ In this study, we examine whether the impact of training on assets and income depends on the delivery mechanism, namely, linkage model type, infrastructure, and training organizer.

In terms of training delivery mechanisms, we are not aware of any study that scientifically investigates these issues. These mechanisms add a second tier to training impact studies. Once it has been established that training has impact, it is important to uncover which mechanisms may support and multiply its impact. The paper contributes to the small number of studies that seek to identify the impact of additional training for borrowers (Karlan and Valdivia, 2009). It also lends itself to the debate of whether microfinance should be narrowly focused on credit or on 'microfinance plus', for instance, provision of additional services like training. Some proponents argue that providing credit is enough, while others contend that credit needs to be complemented with marketing and business skills. Still, others find microfinance not as an end per se but as a vehicle for achieving other development goals such as education and health.

¹ See Bali Swain and Varghese (2010)

The paper begins by examining the impact of training on assets and income. It looks at different vectors by investigating the impact of the quantity of training, in terms of the amount of weeks of training on the borrowers. It then turns to training interactions: whether training is more effective in villages with better infrastructure. Finally, it examines delivery systems to find which linkage type and training organizer delivers the greatest impact for training.

We begin by correcting for participation bias only with the pipeline method (Coleman, 1999). These results show that training has no effect on assets, but positively impacts income. However, members may choose to participate or not in a training program that introduces a selection training bias. We therefore correct for both the participation and the training bias with regression adjusted methods. Corrected results reverse the original results and show that training is in fact more effective for asset accumulation than for income. These results indicate that borrowers who choose to train are those with greater income and lower amount of assets which produces the original results where we only account for membership selection.

Even though in general, training has greater impact on assets than income, the impacts would be heterogeneous depending on the delivery mechanism. We then turn to the objective of the paper and examine the impact of delivery mechanisms. We properly account for both membership and training bias with regression adjusted methods. The impact of assets has greater effect in villages with better infrastructure. Income impact of training is least when banks form and link groups (linkage model 1). We also find that NGOs organized training has strong impact on assets. Our results are robust for sensitivity to unobservables.

On Indian SHGs specifically, impact studies consist of the Puhazendhi and Badataya study (2002) commissioned by NABARD (India's rural development bank) and the recent NCAER (2008). Both studies measured impact by computing the percentage difference of the means of members' variables pre and post SHGs membership. Clearly, this type of analysis does not account for any changes in observable characteristics nor broad economic changes through a control group. However, due to the scarcity of evaluation of SHGs, these studies have had much policy influence, and are widely quoted in a number of Reserve Bank of India (RBI) and National Bank for Agriculture and Rural Development (NABARD) documents.

For those unfamiliar with SHGs, we present the program details and the information on the linkage models and the training provided by the SHGs. Section three discusses the methodology and explains potential biases. In the fourth section, we describe our data set with the results presented in section five. In the last section, we conclude and draw some policy lessons.

2. Self Help Groups, Training, and Delivery Mechanisms

Self Help Promoting Institutions (SHPIs) help form a SHG with ten to twenty members (usually women). The members then have to save for six months and if the bank deems the group as credit worthy, it links to the group. The banks then disburse loans for generally four times the accumulated savings, which the group in turn lends to its own members. The group members hold meetings, and collect and provide repayments to the nearest bank branch. SHPIs consist of NGOs, individuals, bank officers, or government officers. Three models of linking self-help groups to banks have evolved over time. Model 1 encourages banks to form and finance self-help groups. Model 2 encourages NGOs to form groups but the groups are financed by the banks. In model 3, NGOs form groups and act as financial intermediaries for the groups. The drawbacks of the models are the following. In Model 1

banks may form groups for the sole reason of receiving bank loans and thus disintegrate more quickly. It also takes time and resources to train and change the mindset of the bank officials to microfinance style lending (as documented by Satish, 2001).

Model 2 is the most popular and can reach poorer borrowers since the groups are formed by NGOs. However, it requires coordination between banks and NGOs. This linkage exploits each lender's comparative advantage with the bank's lending and NGOs focusing on group formation and training. In Model 3, NGOs that are more like MFIs can exploit their advantage by lending on their own but the burden of lending falls on themselves. We anticipate the greatest impact for model 2, where each institution follows its comparative advantage. The least impact should arise for model 1, since the bank officials form groups with limited experience while in model 3, the NGOs that partake have had some experience in lending.

If the village infrastructure cannot support training, then training may not translate into better outcomes. For instance, lack of proper roads negatively impact communication and connectivity and may hamper the organization of a training camp within that village, or the possibility of finding a trainer who would be able to commute to the village easily. Trainers do not reside in the particular village but would travel to the village through transportation which is aided by access to paved roads. We examined different variables to see which would affect the impact of training. We find that of all the infrastructure variables, only distance from paved road matters.² Recent research on the impact of rural roads finds similar evidence (see Estache, 2010). Thus, training effectiveness requires infrastructure in place to support the impact of training.

² We also examined distance from market, bus-stop, primary health care center, and market. We found no impact of these infrastructure variables.

We further examine whether who organized the training had positive impact. Either a government official or worker or an NGO provided training.³ If training is organized and conducted by NGOs, members might sustain and carry out the directives of training programs better. We can broadly classify training into two categories. First, general training to all SHG members which covers aspects of group formation, book-keeping and introduction to linkage methods. The second training module relates to skill formation. This study will mainly focus on this aspect of training. The skill formation training aims at improving income-generating activities such as farming, craft or business and is mostly provided to SHGs that are already credit linked. SHG members may voluntarily choose to participate in this type of training (hence, the resulting selection bias).

SHG members can demand the required skill training. However, their demand may not be met in all the cases because the viability of the training sessions require a critical number of potential trainees. Moreover, local trainers for that specific skill also need to be found. NGOs in particular also provide additional education, health related training and awareness creation training. However, not all SHGs provide this type of training, nor is the type of program homogenous.

3. Estimation Strategy

In this section, we limit our remarks on impact assessment to those pertinent to this paper.⁴ We will first establish the correction for selection into the program and then discuss the treatment of training. For SHGs, certain difficulties arise. The randomization method adopted by Karlan and Valdivia (2009) is difficult to implement. For large programs such as SHGs, it would entail synchronizing the training randomization across different states. A

³ The category “others” included bank officials, friends and relatives, and anyone else. However this represented only 1 % of the organizers.

⁴ Selection bias in impact studies has been discussed at length in Karlan and Goldberg (2006).

second strategy (as adopted by Pitt and Khandker, 1998) exploits an exclusion rule on credit access to estimate unbiased impact. However, SHGs follow no such exogenous rule. We follow another method, the pipeline approach. By design, SHG members have to wait to receive a loan from the bank (about six months). We exploit this design feature to identify the self-selected members who have not yet received a loan.

NABARD's choice to expand the SHG program occurs at the district level without any specific announced policy targeting certain villages over others.⁵ We have data from ten districts in five different states of India, where some respondents have been SHG member for at least one year. In the same districts (but different villages), members from newly formed SHGs that have as yet not received financial services from the bank, have also been selected. Thus, the treatment group in our sample consists of mature SHG members, while the new SHG members form the control group.⁶ To account for the remaining village level variability, we employ village level characteristics.⁷

Program placement bias arises from non-random placement of programs. This may arise from placement of programs in regions that are relatively better-off in terms of economic development and infrastructure and may produce better impact outcomes. This same problem affects training programs. As described above, we hold these differences constant by drawing the treatment and control group from the same area, i.e. the same district.

As mentioned in the earlier section, the SHPIs provide training to all SHGs. The training variable (T_{ijs}) indicates whether the household received training. Thus, this variable

⁵ NABARD's or the bank's decision to link with a SHG might follow the NGO's choice. We do not have information whether NGOs favor certain villages over others within a certain district.

⁶ We do not have data to actually test this hypothesis since otherwise we condition on the unobservables. For observable differences, we did not find any significant difference between old and new groups.

⁷ The dropout rate for SHGs is not severe in that the NCAER study (2008) estimated the dropout rate as 8.2 %, below the 20-30 % cited by Aghion and Morduch (2005) and Karlan and Goldberg (2006) as a severe problem.

captures whether training has impact beyond membership duration and self selection of the members. The potential endogeneity of this variable is discussed later.

We first estimate the following equation:

$$I_{ijs} = a + \alpha X_{ijs} + \beta V_{js} + \lambda D_s + \gamma M_{ijs} + \delta SGHMON_{ijs} + \phi T_{ijs} + \eta_{ijs} \quad (1)$$

where I_{ijs} is the impact for household i measured in terms of asset creation or income generation, for household i in village j and district s , X_{ijs} are the household characteristics; V_{js} is a vector of village-level characteristics, and D_s is a vector of district dummies that control for any district level difference. Here, M_{ijs} is the membership dummy variable, which controls for the selection bias arising from participation in the SHG program. It takes the value one for both mature and new SHGs. It takes the value of zero for those villagers that have chosen not to access the program. Here, $SGHMON_{ijs}$ is the number of months that SHG credit was available to mature members, which is exogenous to the households. The parameter ϕ measures the impact of training. However, this parameter is biased as it does not account for the training endogeneity.

To account for both training endogeneity and the participation bias we use propensity score matching and then test the sensitivity of our results to unobservables.⁸ Propensity score estimators match the households who received training to those who did not. Except for the treatment, the matched households are very similar. Households with low or high probabilities cannot be matched and generally are dropped. In matching terminology, we keep the households on the common support. The probability $P(X)$ of being selected is first determined by a logit equation and then this probability (the propensity score) is used to match the households. Y_1 is the outcome variable of interest for

⁸ See the excellent survey by Caliendo and Kopeinig (2008) on the main issues on propensity score matching. For estimation of Average Treatment Effects Based on Propensity Score see Becker and Ichino (2002).

those with training ($T=1$), and Y_0 is the outcome variable of interest for those without training ($T=0$), thus equation (2) denotes the mean impact of training:

$$\Delta = E[Y_1 | T = 1, P(X)] - E[Y_0 | T = 0, P(X)] \quad (2)$$

where the matched comparison group provides the data to calculate the second term, and the propensity score weights the whole expression for all households on common support.

In order to account for the SHG participation bias, we employ the regression adjusted matching estimators as in Heckman *et al.* (1997) (hereafter, HIT). These allow for different covariates for the logit participation equation and the outcome equation. In our case these estimates are particularly important because of the need to account for the selection of participation into the program using the pipeline method.⁹ The following procedure explains the steps for regression adjusted matching estimators. First, run a regression for the outcome equation on the no training group $Y_0 = x\beta + \epsilon$. Then calculate the fitted values.¹⁰ Second, subtract these values from the outcome variables for both the no training and training group (since these fitted values are free of the effect of training). Third, match the new variables, outcome variables minus the fitted values. The estimator is given by equation (3):

$$\Delta_{RAM} = \sum_{i=1}^T w_i \left[(Y_{1i} - x_i \hat{\beta}_0) - \sum_{j=1}^C w_{ij} (Y_{0j} - x_j \hat{\beta}_0) \right] \quad (3)$$

⁹ We are aware that this specific type of selection is actually a sequential or dynamic selection process. In other words, the subsequent choice of training depends upon the effect of participation on income or assets. But as Caliendo and Kopeinig (2008) state: 'practical experiences with sequential matching estimators are rather limited' we estimate the static framework with matching for the training selection problem.

¹⁰ HIT suggest a semi-parametric procedure which exploits a richer functional form. We attempted to fit this from our data with two candidates, age and SHGMON. We failed to reject the null hypothesis of linearity: $P=0.664$ and $P=0.552$ respectively for age and SHGMON.

where RAM refers to regression adjusted matching estimators, T (C) refers to the total number of treated (not treated), and w (W) refers to the particular weight used in matching for the treatment (control).

For regression adjusted matching, we use the local linear regression (LLR) matching algorithm (for bandwidths 1 and 4). The theorems in HIT which justify regression adjusted matching are based on LLR, a generalized version of kernel matching which allows faster convergence at the boundary points. The LLR method uses the weighted average of nearly all individuals in the control group to construct the counterfactual outcome.

4. Data

The data used for the empirical analysis in this paper were collected by one of the authors and forms part of a larger study that investigates the SHG-bank linkage program.¹¹ The household survey uses a pre-coded questionnaire to collect cross-sectional data for two representative districts each, from five states in India, for the year 2003.¹² The sampling strategy randomly chose the respondents from the SHG members at the district level. The non-members were chosen to reflect a comparable socio-economic group as the SHG respondents. For further details on the sampling strategy, refer to Bali Swain and Varghese (2010). The analyses are based on information on 841 observations.

The data were not collected specifically for a training study. We primarily have information on the total training weeks that a household has received. We set the training variable to 1 for all households who reported positive weeks of training. Since both mature

¹¹ The process involved discussion with statisticians, economists and practitioners at the stage of sampling design, preparing pre-coded questionnaires, translation and pilot testing with at least 20 households in each of the 5 states (100 households in total). The questionnaires were then revised, reprinted and the data collected by local surveyors that were trained and supervised by the supervisors. The standard checks were applied both on the field and during the data punching process.

¹² These states (districts in parentheses) are Orissa (Koraput and Rayagada), Andhra Pradesh (Medak and Warangal), Tamil Nadu (Dharamapuri and Villupuram), Uttar Pradesh (Allahabad and Rae Bareli), and Maharashtra (Gadchiroli and Chandrapur).

members and new members received training, we can differentiate the impact of training from that of loan access.

The survey yields other measures of training. When comparing the means and variances of the training weeks for old and new SHGs we find a significant difference: the amount of training weeks (1.52 versus 1.15) and variability in training is larger for mature SHGs (2.42 versus 1.87).¹³ About half (48 per cent) of the mature SHGs received training while 39 percent of the new SHGs reported the same.¹⁴ These statistics are not surprising in that the longer length of membership of mature SHGs will provide them with more opportunities for training. Surprisingly, a sizeable percentage of new SHGs are receiving training indicating a new commitment by policymakers.

Table 1 summarizes the training statistics by model type. Interestingly, under Linkage 1 where banks form SHGs, the largest proportion of members receive training but under the more popular Linkage 2 where NGOs form SHGs, the training period is longer per member. NGOs dominate training organization, even in Linkage 1. Other characteristics such as those of training/non training members as well as mature/new members are available from the authors but we omitted them here for the sake of brevity.

We accumulate assets from six categories: land owned, livestock wealth, dwelling and ponds, productive assets, physical assets, and financial assets (includes savings and lending). Household income includes income from agriculture, poultry and livestock, wages, fisheries and forest resources, rent, remittances, and enterprise. Household characteristics include age, gender, education dummies and number of earning members in the family. We

¹³ A t-test with unequal variances revealed a t-ratio of 3.32 statistically significant at the 1 % level.

¹⁴ NCAER (2008) also finds that nearly half of all the SHGs have had skill development training. About 35 per cent of the households received training only once in 2006 and another 15 per cent have received training multiple times.

Table 1
Training statistics (by linkage model)

Training Statistic	Model 1	Model 2	Model 3
Received training (%)	55	43	48
Length of training (weeks)	2.5 (1.4)*	3 (1.9)*	2.3 (1.5)*
Government training (%)	6.5	11.4	2.4
Training by NGOs (%)	89	70	76
Training organized by others (%)	0	1	0

Notes: *Mean (standard deviation)

have greater (lesser) incentive for asset accumulation (income generation). In order to control for initial wealth, we employ land owned three years ago.¹⁵ For village characteristics, in addition to male wage, we include the following distance variables: paved road, market, primary health care center, and bus-stop.

5. Results

This section discusses the estimation results for the effect of linkage model type, infrastructure, and training organizer on the training impact SHG participation. We first examine the results through regression methods, which serve as points of departure. Furthermore, these can be fully interpreted, along with the impacts of the covariates and interactions. We then compare these results to those obtained through matching methods. Table 2 provides the regression results of Equation (1) for the impact of training on assets and income. Columns (3) and (4) focus on the amount of training received by SHG members and its impact on the gross assets and income. The regression estimates indicate that

¹⁵ Since land forms the bulk of assets and land turnover is infrequent in India (see Pitt and Khandker, 1998, for more discussion on this observation), this variable was the best choice for initial wealth.

Table 2

Regression estimates of impact of training on asset creation and income ($\times 10^{-2}$)

	(1) Gross Assets	(2) Income	(3) Gross Assets	(4) Income
Member	-459.02 (2.32)**	19.38 (0.92)	-437.71 (2.28)**	25.48 (1.24)
SHGMON	6.34 (1.93)*	-0.74(1.68)*	6.37 (1.92)*	-0.72 (1.66)*
Training (Yes=1)	108.99 (1.18)	27.13 (1.83)*	----	----
Weeks of Training	----	----	14.87 (0.76)	3.01 (1.03)
Age	1.17 (0.20)	1.28 (2.08)**	1.25 (0.21)	1.31 (2.13)**
Gender (Female=1)	101.17 (0.76)	-0.53 (0.02)	100.84 (0.76)	-0.88(0.03)
Dep. Ratio	402.15 (2.13)**	-109.8 (3.32)***	403.56 (2.15)**	-109.7(3.32)***
Primary Ed.	234.22 (1.92)*	-19.28 (1.10)	233.06 (1.90)*	-19.58 (1.11)
Secondary Ed.	292.87 (2.43)**	-33.15 (2.22)**	287.54 (2.36)***	-34.32(2.31)**
College Ed.	566.93 (2.09)**	-55.65 (1.70)*	567.37 (2.09)***	-55.50 (1.69)*
Land 3 years ago	423.55 (7.89)***	16.04 (2.74)***	426.00 (7.99)***	16.73(2.86)***
Distance Paved Rd.	-74.96 (2.43)***	-0.27(0.08)	-77.53 (2.53)**	-1.04(0.30)
Distance Bank (kms.)	8.33 (0.72)	-0.92 (0.72)	7.93 (0.69)	-1.06(0.81)
Distance Market	-17.59 (1.57)	-0.002(0.00)	-18.22 (1.62)	-0.14(0.06)
Distance HealthCare	16.65 (0.68)	-1.83(0.66)	17.86 (0.72)	-1.54(0.55)
Distance Bus Stop	46.92 (1.53)	-1.03 (0.32)	47.91 (1.58)	-0.63(0.19)
Male Wage	-4.93 (1.07)	-0.02(0.03)	-4.85 (1.05)	-0.003(0.01)

Notes: *** Significant at the 1 % level. ** Significant at the 5 % level. * Significant at the 10 % level. All regressions include district fixed effects. Analysis based on 841 observations. Absolute t-ratios in parentheses computed with White heteroskedasticity-consistent standard errors clustered by village. See text for definitions of variables.

training positively impacts income but not assets. However, membership positively impacts assets and negatively income. The length of training has no direct impact on either income generation or asset creation. The results indicate that training may be more effective with a focused delivery, that is, higher quality and diversity.

The impact of the level of infrastructure and business training with their respective interactions is presented in Table 3. Columns (1) and (2), find that training has a much higher impact on assets when made available to SHGs in villages closest to paved roads. For effective training impact on assets, location of village matters and households benefit from better market connectivity. For those with training, one kilometer less of paved road can drop assets by about 5000 rupees. With income generation, we do not observe a similar impact, presumably because households may consume their own products without relying on the market. By linkage type (with the omitted category model 2), model 3 has the most perverse effect on income. However, as expected model 1 combined with training negatively affects income. Finally, training organizer matters. Training held by the government can negatively affect asset accumulation.

The regression results, though suggestive, do not correct for training endogeneity. Regression adjusted matching estimates that correct for endogeneity show a stronger impact on assets but none on income (see Table 4). This suggests that those who received training had greater income beforehand. Columns (3) and (4) indicate that infrastructure matters, as members located in villages closer to paved roads benefit with a positive impact on assets with training.

Table 3

Estimates of impact on asset creation and income with respect to infrastructure, type of model and training provider ($\times 10^{-2}$)

	(1)	(2)	(3)	(4)	(5)	(6)
	Gross Assets	Income	Gross Assets	Income	Gross Assets	Income
Member	-464.62** (2.35)	33.06 (1.27)	-444.8** (2.22)	41.54 (1.58)	-434.4** (199.99)	36.82 (31.02)
SHGMON	6.35* (1.94)	-0.67* (1.73)	58.51* (1.82)	-0.90** (2.30)	5.96* (3.37)	-0.70 (0.42)
Training (Yes=1)	252.19* (1.88)	34.37* (1.92)	66.50 (0.63)	31.93** (2.13)	184.26 (188.64)	0.62 (29.76)
Distance Paved Rd. (kms.)	-78.20** (2.66)	0.24 (0.06)	-	-	-	-
Distance Paved Rd.* Training	-48.74** (1.99)	-2.48 (0.62)	-	-	-	-
Model 1	-	-	-193.1 (0.78)	41.56 (1.50)	-	-
Model 3	-	-	14.59 (0.13)	-45.52* (1.89)	-	-
Model 1*Training	-	-	29.49 (0.06)	-73.47* (1.76)	-	-
Model 3*Training	-	-	171.5 (0.84)	-6.89 (0.21)	-	-
Organised by NGO	-	-	-	-	-54.33 (92.01)	-24.74 (40.68)
Organised by government-program	-	-	-	-	-69.31 (196.92)	-25.88 (25.54)
NGO organised*Training	-	-	-	-	-4.00 (208.33)	33.28 (33.06)
Govt. organised*Training	-	-	-	-	-907.02** (386.5)	27.89 (49.05)

Notes: ** Significant at the 5 % level. * Significant at the 10 % level. All regressions include household characteristics and village level characteristics as in Table 3 and district dummies. Analysis based on 841 observations. For (1), (3), and (5) absolute t-ratios in parentheses computed with White heteroskedasticity-consistent standard errors clustered by village. Regressions (2), (4), and (6) are Tobit regressions. See text for definitions of variables.

Table 4

Regression adjusted matching estimates of training impact on assets and income, and by infrastructure ($\times 10^{-2}$)

Matching Algorithm	Training		Dist. from paved road	
	(1) Gross Assets	(2) Income	(3) Gross Assets	(4) Income
LLR (bw 1) (S.E.)	201.2** (1.99)	8.2 (0.6)	334.2* (177.5)	70.8 (131.0)
LLR (bw 4) (S.E.)	201.2** (2.12)	8.2 (0.6)	334.2* (174.2)	70.8 (137.6)

Notes: ** Significant at the 5 % level. * Significant at the 10 % level. LLR= local linear regression, p-values in parentheses standard errors created by bootstrap replications of 200. ^aCovariates of regression same at Table 2, (1) and (2), omitting the training variable. See text for definition of variables. Number of observations on common support are 742.

Table 5

Regression adjusted matching estimates of training impact on assets and income by linkage Model ($\times 10^{-2}$)

Matching Algorithm	Model 1		Model 2		Model 3	
	(1) Gross Assets	(2) Income	(3) Gross Assets	(4) Income	(5) Gross Assets	(6) Income
LLR (bw 1) (S.E.)	247.8 (501.6)	-122.8** (50.8)	116.8 (119.5)	27.2 (18.5)	227.1 (171.2)	45.1* (26.8)
LLR (bw 4) (S.E.)	247.8 (499.1)	-122.8** (57.2)	116.8 (110.1)	27.2* (15.5)	227.1 (158.9)	45.1* (26.1)

Notes: ** Significant at the 5 % level. * Significant at the 10 % level. LLR= local linear regression, p-values in parentheses standard errors created by bootstrap replications of 200. ^aCovariates of regression same at Table 2, (3) and (4), omitting the training variable. See text for definition of variables. Number of observations on common support are 742.

Table 5 indicates that a breakdown by linkage type has no effect on assets. However, when banks form groups this harms income generation. Linkage models 2 and 3 (where the NGOs are actively involved) positively impact income.

Finally, training organizer and leaders matter. As results in Table 6 suggest, when NGOs organize training we find a strong impact on assets. Training organized by government officials does not show any impact. To check robustness of our results we conducted sensitivity analyses of our results to unobservables (Ichino *et al.*, 2007). Our results are robust to these analyses (available on request from the authors).

Table 6
Regression adjusted matching estimates of training impact on assets and income by training provider (x10⁻²)

Matching Algorithm	Training by NGOs		Training by Govt.	
	(1)	(2)	(3)	(4)
	Gross Assets	Income	Gross Assets	Income
LLR (bw 1) (S.E.)	387.1*** (11002)	18.75 (1366)	-469.07 (37314)	66.96 (7032)
LLR (bw 4) (S.E.)	387.1*** (12639)	18.75 (1459)	-469.07 (36047)	66.96 (6619)

Notes: ** Significant at the 5 % level. * Significant at the 10 % level. LLR= local linear regression, p-values in parentheses standard errors created by bootstrap replications of 200. ^aCovariates of regression same at Table 2, (5) and (6), omitting the training variable. See text for definition of variables. Number of observations on common support are 742.

In sum, with regression adjusted matching results (which correct for both training and membership endogeneity) we find a strong impact overall on assets but not on income.

Furthermore, infrastructure and organizers of training matter in that they would positively impact training delivery. Thus, regression adjusted matching results reveal that correctly adjusting for both member and training selection bias offers starkly different results on the impact of training. These results are robust to departures from our specification.

6. Conclusion

We evaluated the impact of training in Self Help Groups on two outcome measures, income and assets. In general, we find that training has a positive impact on assets. The quantity of training as in weeks does not make any difference on either outcomes. Good village infrastructure helps training's effectiveness in asset accumulation. When NGOs help form SHGs and banks finance groups, training has the greatest impact on income.

This study also yields some programmatic lessons. Linkages between banks (even public sector ones) and NGOs may provide effective means for credit delivery. Banks provide the loans and NGOs provide the organization (as in Linkage Two) or banks finance NGOs who provide loans (as in Linkage Three). The results here call for an expansion of these types of linkage and for avoiding the use of government officials as training organizers in the SHG bank linkage program.

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