Asset transfer and child labor: Evidence from a field experiment in Bangladesh

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Introduction

Child labor has drawn a considerable attention in recent public policies and research studies because of its violation of basic human rights and its long-term negative consequences on household economic growth and child development outcomes (Edmonds 2008). It can reduce children current educational achievement as well as future income potential. Beegle, Dehejia, and Gatti (2005) analysed a panel data from Vietnam and compared educational outcomes of children who are involved with market work and studies versus those who only study. They find that an additional hour of work decreases the probability that a child will be in school after five years by three percentage points. They also find that it declines approximately twenty-two days' grade attainment. Ilahi, Orazem, and Sedlacek (2000) observe wage rates of eighteen plus year workers in Brazil and find that the wage rate is 13 to 17% lower for those who entered the labor market before thirteen years compared to those who entered in later ages.

Household asset holdings and standards of living are key determinants of child labor along with other factors, for example, parents' education and social norms. Some studies show that child labor decreases with household asset holding (Blunch and Verner 2001) while other studies show that child labor can increase with asset holding (Gautam and Sarangi 2005, Bhalotra and Heady 2003, and Rogers and Swinnerton 2004). One of the main challenges in determining the causal relationship between child labor and asset holdings is that poor households differ from rich households, which brings potential omitted factors biases (Edmonds 2005). Some studies use variation in household income excluding the child income, and others use instrumental variable approach. Both methods have their own limitations. The first approach does not deal with the joint determination of asset holding/living standard and child activity choices. The validity of the second approach largely depends on a strong assumption that the instrument is related to asset holdings but has no direct effect child labor, an assumption which is unlikely to hold in many cases. Therefore, it is ideal to study child labor and household asset holding with some exogenous variation in asset level.

We use data set from a large scale randomized control trial (RCT) experiment to study the relationship between household asset holdings and child labor in Bangladesh. The program transfers livestock assets and subsistence allowances to very poor households with an objective to transform the economics life of the households. Similar programs have been implemented in a number of others countries as well and research studies have shown positive impacts of asset transfer on different dimensions of household well-being such as food security, consumption, self-employment activities, cash savings, per capita income, and psychological status of the targeted households (see Hulme and Moore 2007, Emran et al 2014, Asadullah, and Ara 2015, Hossain et al. 2015, Bandiera et al. 2016, Bauchet et al. 2015, and Banerjee et al. 2015).

Although few studies explore the effect of randomized asset transfer intervention on child time allocation, their findings are not conclusive. Benerjee et al. (2015) find no significant effect of the asset transfer on the child time allocation in India, they rather find an opposite result than ours, the children in the treatment group studies 30-40 more minutes per day compared to the control group. Bauchet et al. (2015) assess the impact of the asset transfer on aggregate labor supply time of both the adult members and the children in various activities and find no significant evidence in productive activities, leisure, and household chores and find a significant effect in animal tending, and wage labor activity. Sulaiman (2015) explores the effect of asset transfer on child school enrollment using the same data as ours. He finds that the program intervention has no effect on school enrollment, but has a positive effect on household educational expenditure. He also finds that the program has a short-term impact on child working hour related to livestock rearing. Bandiera et al. (2016) find that child working hour has increased in livestock rearing and land cultivation after an asset transfer in Bangladesh.

Our study exploits the RCT set up to estimate the program impact on child labor indicators, specifically, we assess the program impact on child work time in various activities including livestock and study. We use the Difference in Difference (DID) estimation method to estimate the program impact on child labor. We find that program intervention has a significantly increased child working hours in livestock activity; children in the treatment group work more than double in livestock activity. A large portion of total hours in livestock activity comes at the cost of study time.

Whether the children work out of curiosity (Sulaiman 2015) or for an economic reason after an asset transfer intervention is an important issue yet to be explored. If children have enough leisure time after or before their study time, they could engage in livestock rearing without hampering their study and at the same time can help their parents in productive activities. Another important argument about child work related to livestock rearing is whether a child works because the targeted women cannot move outside of homestead area due to social norms or not. If the targeted women cannot move outside of home freely, they are more likely to ask their children to take care of livestock for herding. We check how much of child working hours in livestock rearing is driven by household income from livestock activity. For the second objective, we estimate how much of total child working hour can be explained by the mobility index of the targeted women. We use a sequential g-estimation following Achariya et al. (2016) and estimate the Average Controlled Direct Effect (ACDE) of the intervention. Our results show that only small fraction of a total child working hour (around 20%)in livestock activity can be explained by income from the livestock sector. We also find an interesting result for mobility index of the targeted women; our result shows that due high mobility index of the targeted women, child worked fewer hours than then they need do in case of low mobility index.

Asset transfer, child labor, and Inverted-U hypothesis

Edmonds (2008) describes four points supporting that child labor might decrease with household income. First, child labor is seen as a bad preference from the parental side; this is similar to the “Luxury axiom” concept proposed by Basu and Van (1998). Second, the utility of marginal income from child work falls. Third, with higher income households can afford to hire labor from market to substitute child labor. Finally, fourth, the opportunity cost of forgone schooling increases with household income as child productivity in schooling activities is positively related to income. A similar argument might hold for asset ownership as household asset holding is a good proxy of household permanent income.

However, the previous points by Edmonds (2008) also depend on other factors. For example, increased income can increase household participation in more income generating activities which not necessarily decrease child labor. Del Carpio, Loayza, and Wada (2016) point out three factors that might increase child labor when households own productive asset. First, hired labor is not a perfect substitute for family labor because of the risks of moral hazard, shirking, and theft (Deolalikar and Vijverberg, 1987; Foster and Rosenzweig, 1994). Second, labor markets may be rigid in rural areas, especially for farm related activities. Third, in some cases, child labor are seen more about enhancing work experience, discipline, and human capital (Beegle et al. 2009; Edmonds 2008; Rogers, and Swinnerton, 2008). Gender dynamics also play a role, for example, Gautam and Sarangi (2005) find that the probability of being child labor differs between boys and girl in Malawi. Bhalotra and Heady (2003) find that girls bear heavier burdens of works compared to boys.

In the context of our program intervention, livestock asset along with subsistence allowance are transferred to the very poor households to lift-up poor women from low productive and wage labor activities. This will bring dynamics in their current activity choices of the targeted women and also of other household members. Child work hour may increase for a number of reasons such as, first, targeted women may continue working in their previous activities, second, targeted women work hour is not enough to take care of livestock and household cannot afford hiring a labor from market, third, livestock needs herding work that typically women cannot do because of social norms which restrict women's movement in going outside of home in Bangladesh, fourth, targeted female participate in economics activates which require rest of the family members, especially children, to work in household chores, and fifth, household might think that children participation in work will make them more disciplined and productive. All these factors will push children to work more and spend less time in study.

Challenging the Frontiers of Poverty Reduction (CFPR) program

BRAC launched the Targeting the Ultra Poor (TUP) program in 2002, targeting asset-poor females, a group that is among the hardest to reach through conventional antipoverty programs and microfinance interventions. The TUP program was built on BRAC's experiences with the Income Generation for Vulnerable Group Development (IGVGD) program launched jointly by BRAC and the World Food Programme (WFP) in 1985. The IGVGD program transferred food and provided skill training to very poor households. Although it was successful in increasing income of the participant households, it failed to generate sustainable impacts (Hashemi 2001), suffered from targeting problems, and program service packages were ineffective (Ahmed et al. 2009). Based on the lessons from the IGVGD program, BRAC introduced TUP, which introduced productive asset transfers and an overhauled targeting strategy.

The second phase of the program was initiated in 40 districts in 2007 named as Challenging the Frontiers of Poverty Reduction (CFPR). The program transfers livestock assets such as cows, goats, and chickens to households with an average value of USD 140. The program also provides training and support for better utilization of the transferred assets. The program also provides subsistence allowances during the first 40 weeks to compensate for any shortfalls in income that might happen because of the occupational shift of the targeted female. The program transfers assets in six different combinations of either one or two types of livestock. Participants are encouraged to retain the transferred asset for at least two years, however, they can exchange current assets for other income generating assets during this period. Skill training includes an initial classroom training, weekly visit of BRAC staff for the first two years, and monthly or bi-monthly visits of livestock specialists for the first year (Bandiera et al. 2013).

BRAC follows a three-stage procedure to identify the participant households in the program. At the first stage, BRAC identifies the poorest districts and sub-districts of Bangladesh using World Food Program (WFP) poverty mapping for Bangladesh. Within each sub-district, the poorest communities are selected in consultation with BRAC staff. In the second stage, a participatory community wealth ranking is formed to identify the poorest household in each cluster. More specifically, communities are divided into clusters of 80-120 households and all the households in each cluster are ranked based on wealth holdings in a participatory approach. All households in the bottom 2/3 categories, termed as "community-defined ultra-poor", are selected for the next stage. In the third and final stage, all the selected households are surveyed to identify who meets at least three out of five inclusion conditions and none of the exclusion conditions. Finally, under the inclusion and exclusion conditions, households are selected for program participation. Inclusion criteria are as follows: a household is dependent on female domestic work or begging, holds less than 10 decimals of land, has no adult active male member, school-aged children are engaged in paid work, or possesses no productive work. Exclusion criteria are as follows: household has no active adult women, is not a microfinance participant, or is not a beneficiary of government or non-government development project.

Sample of the study

We use data set from a randomized control trial (RCT) impact evaluation study launched in 2007 to evaluate BRAC CFPR program. A multi-stage sampling procedure has been followed in accordance with the targeting strategy of CFPR program. The evaluators randomly selected 1 or 2 sub-districts from each district and then one BRAC branch office is randomly selected as treatment branch and one as control branch within each sub-district. Finally, the poorest communities from each branch are selected for the experiment. The final evaluation covers 20 sub-district, 40 branches, and 1,409 communities. The original experiment uses information of 7,953 eligible households to evaluate the effect of the CFPR intervention. All the households are interviewed in 2007, 2009, and 2011.

Household in the baseline

Out of 7,953 households, we find 1,176 has at least a child aged between 5 to 14 in 2007. Among the total number of children is 1,635 and 2,452 in control and treatment group, respectively. Table 1 shows pre-program intervention working hours in the treatment and the control groups and their mean differences. It is expected that the baseline differences between groups will be insignificant as it will demonstrate the credibility of randomization. We find that for all the outcome variables, there is no significant difference between the treatment and the control groups.

[table 1 here]

Impact identification strategy

We estimate program impact using intent-to-treat (ITT) estimate by comparing all households with children in both treatment and control groups. The following Difference in Difference (DID) specification are used,

$$Y_{it} = \delta d_t + \gamma\ CFPR_i + \beta_t (CFPR_i \text{ X } Post_t) + \varepsilon_{it} \tag{1}$$

where Y_{it} is work hours for child i at time *t*. d_t time and location dummy, $CFPR_i$ is a treatment dummy indicator and W_t is a time dummy indicating 2009 or 2011. β_3 identifies the program impact on child's working hours for the midline (2009) and the end line (2011). We control for branch level fixed effects in the model; this is expected to improve efficiency because the randomization is placed at the branch level (Bruhn and McKenzie 2009). In addition, all the standard errors are clustered at the branch level to adjust for the intra-cluster correlation within a branch.

Estimation of controlled direct effect

To estimate whether an increase in child labor is due to an economic reason or not, we can estimate the amount of program impact mediated through an economic variable (say K). We can control K and an interaction of K with treatment indicator in equation 1, which will indicate how of the program effect have worked through K. However, one major problem of such a regression model is that K is a post-treatment variable; that is K is also affected by the program intervention. Therefore, it will generate biased estimation as both the post-treatment variable and the child labor variable can be determined by a same unobservable factor(s) not included in the regression model. Acharya et al. (2016) give a detailed explanation on how controlling a post-treatment variable can bias estimators away from zero. As a solution to this problem, they introduce a *sequential g-estimation* method, which can estimate the direct effect of an intervention at some value of K. Under sequential unconfoundedness and no intermediate interaction assumptions[1], the *sequential g-estimation* method can be represented by the following two stages,

Stage 1: Estimate equation 1 controlling for K and predict Y_{it} that is explained by K as follows,

$$(1)\qquad \begin{aligned} Y_{it} &= \delta_{dt} + \gamma TUP_i + \beta_t (TUP_i \times post_t) + \xi K_{it} + \eta_t (post_t \times K_{it}) + \varepsilon_{it} \\ \hat{Y}_{it} &= \hat{\xi} K_{it} + \hat{\eta}_t (post_t \times K_{it}) \end{aligned}$$

Stage 2: Estimate program impacts on Y_{it} net of $\hat{Y}_{it}$ as follows,

$$(2)\qquad \begin{aligned} \tilde{Y}_{it} &= Y_{it} - \hat{Y}_{it} = Y_{it} - \hat{\xi} K_{it} - \hat{\eta}_t (post_t \times K_{it}) \\ \tilde{Y}_{it} &= \delta_{dt} + \gamma TUP_i + \beta_t (TUP_i \times post_t) + \varepsilon_{it} \end{aligned}$$

β_t will show the average CDE.

Impact on child working hours

Table 2 shows the impact of CFPR intervention on child working hours in different earning activities and on study time. The result shows that the CFPR intervention has increased children time allocation in livestock activity and decreased study time. The treatment group, on average, work 89 hours more per year in livestock activity in the midline and 53 hours more per year in the end line compared to the control group. Children in the control group work on average 41 hours in livestock activity in the midline, which is almost 212% less compared to the children in the treatment group. Although time allocation in livestock activity has decreased in the end-line, it is still 123% more in the treatment group compared to the control group. The result shows that study time has decreased only in the midline, and the total hour decreased from the

[1] The sequential unconfoundedness assumption holds if the selection-on-the-observables condition holds for both the outcome variable and K.

study is higher than total hour increase in the livestock activity. Therefore, it is possible that the children in the treatment group have allocated forgone study time in multiple activities.

We categorized children into two groups by age: aged between 5 to 10 and aged between 10 to 14. Children aged between 5 to 10 are usually studying at primary level who require less time in school and to study compared to the student at the secondary level (aged 10 to 16). Results are shown in table 3 in panel A and B, respectively. We find that children aged between 5 to 10 from the treatment group work 46 hours more in the midline and 30 hours more in the end line compared to the children of a same age in the control group. Table 3 also shows that impacts are much higher for the children aged between 10-14 years for similar activities. We also find that girls sacrifice more study time and work more hours in household activities compared to boys after the program intervention (table 4).

[Table 3 here]

[Table 4 here]

Impact on other household members

We also estimate program impact on time allocation on targeted female and other working aged members. Table 5 shows that the CFPR intervention increased working hour of the targeted female in livestock activities both in midline and end-line. Targeted female in the treatment group works almost 551 more hours per year in the midline and 446 more hours in the end-line compared to the targeted female in the control group. Results also show that the targeted female increase their time allocation in agricultural self-employment activities and decrease in servant/maid related works in the long-run. A similar result is also noticeable for other working members as presented in table 6. Results show that other working members in the treatment area also increased their time allocation in livestock activity. Table 6 also shows that other working members also increased their time allocation in non-agricultural self-employment activities and decreased study time both in the medium term and long term. Like the targeted female, we find that the other working members spend more time in agricultural self-employment activity in the long run.

[Table 5 here]

[Table 6 here]

From the time allocation results of children, targeted female, and other working members, we notice that all the household members allocate more time in livestock activity. Children and other working members spend less time in study. Working aged members including the targeted female work more hours in self-employment activities over time.

The average controlled direct effect

Table 7 shows how much of the total effect of the CFPR intervention can be explained by household income from livestock activity. Column 1 and 2 show effect for all the children and the subsequent column shows the result for children at primary, secondary, boys, and girls, respectively. Our results show that after subtracting out the effect of livestock income, the CFPR intervention still has a large impact on child labor. Specifically, our results show that 80% of total impact can be explained by non-economic factors and only 20% of the impact are due to income from livestock activity in the midline. The contribution of the economic reason has increased in the long run as expected; 50% of the total impact are due to economic reason in the long run. We get similar and consistent results for children at primary and secondary level. The same argument also holds for boys are girls except that girls work in livestock only for non-economic reason in the long-run.

Table 8 shows how much of the total effect of the CFPR intervention can be explained by mobility index of the targeted female. As before, column 1 and 2 show effect for all the children and the subsequent column shows the result for children at primary, secondary, boys, and girls, respectively. We find that after subtracting out the effect of mobility index, the effect of the CFPR intervention has increased compared to the effect without controlling for mobility index. This implies that the TUP intervention has increased mobility of the targeted female, which in turn enabled them to work more hours in livestock activities and reduced their dependency on children for outside herding activity. As a result, children in the treatment group needed to work fewer hours compared to the scenario where the CFPR intervention has no effect on mobility. Our results show that the effect of the CFPR could have been 184 hours per year instead of 83 hours in midline had there is no improvement in mobility of the targeted female. Similarly, total impact could have been 117 hours instead of 51 hours in the end-line. We find a similar result for disaggregate categories as well.

[Table 7 here]

[Table 8 here]

Conclusion

Asset transfer programs are largely successful in transforming the livelihoods of the "ultra-poor" household in terms of occupational change, asset holdings, consumption, and food security, unlike the other microfinance programs that largely fail to generate strong positive evidence on borrowers' welfare (see Benerjee at al. 2015 for details). It works as a big push for the "ultra-poor" households to overcome the poverty traps. However, such an opportunity also induce household to employ their children in working activities to reduce production cost and maximize household earnings. Social norms sometimes hinder women movement outside of the homestead area which can also cause an increase in child labor.

Our finding shows evidence of increased children’s working hours after the asset transfer and importantly reduce children study time in some cases. Children who get involved in working activities once might continue their works for the longer term and shift to more income generating activities in the future. Such early involvements can bring long-term negative consequences on human capital, health, and economics outcomes of the household. It is, therefore, important to introduce additional incentive packages in the asset transfer intervention that will discourage the “ultra-poor” households to involve their children in working activities.

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Table 1. Baseline Characteristics by treatment status

	Control		Treatment			
	Mean	Std. dev	Mean	Std. dev	Mean diff.	P-value
Household activity	62.78	274.07	55.50	258.40	-7.28	0.63
Wage labor	41.17	268.18	42.54	270.10	1.38	0.92
Livestock rearing	35.92	159.96	30.40	148.02	-5.52	0.65
Agricultural self-employment	7.26	87.06	7.69	94.08	0.43	0.88
Non-agricultural self-employment	49.04	337.06	54.43	360.25	5.39	0.66
Study	898.90	606.12	867.47	590.38	-31.43	0.62

Note: Number of children in control group is 1,635 and 2,452 in treatment group. All the standard errors are cluster at the Branch level to estimate P-value.

Table 2. Program impact on children working hours (Yearly/hour)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Household Activity	Wage Work	Livestock	Agricultural Self-employment	Non-agricultural Self-employment	Study
Treatment X 2009	5.222	5.468	83.861***	5.751	-0.478	-186.887**
	[15.078]	[15.389]	[17.136]	[4.508]	[10.062]	[87.988]
Treatment X 2011	6.569	-1.558	52.555**	3.459	2.508	-46.315
	[15.534]	[12.876]	[20.183]	[3.536]	[12.404]	[136.206]
Constant	20.480**	15.578	11.190	2.748	32.904***	859.578***
	[8.624]	[11.595]	[10.967]	[1.823]	[7.935]	[36.114]
Control mean (2009)	57.05	40.13	41.03	8.23	8.21	1290.02
Control mean (2011)	41.43	42.27	43.22	5.87	29.50	1428.05
Observations	12,541	12,541	12,541	12,541	12,541	12,541

Note: All the standard errors are cluster at the Branch level to estimate P-value. Sub-district level fixed effects are controlled in each regression. Standard errors are clustered at the branch level.

Table 3. Program impact on children working hours by education level (Yearly/hour)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Household Activity	Wage Work	Livestock	Agricultural Self-employment	Non-agricultural Self-employment	Study
Panel A: Child at Primary level (aged 5-10 years)						
Treatment X 2009	1.330	8.404	42.522***	8.678**	-11.453	-190.784*
	[9.098]	[7.349]	[13.301]	[3.335]	[8.306]	[99.806]
Treatment X 2011	4.615	-0.200	29.782*	8.295**	-9.431	1.569
	[9.625]	[7.936]	[15.798]	[3.443]	[10.289]	[156.859]
Constant	10.864**	3.018	51.859**	4.278**	-2.334	805.311***
	[5.281]	[4.153]	[21.801]	[2.027]	[3.062]	[96.543]
Control Mean (2008)	16.26	0.83	18.59	0.63	1.84	1377.61
Control Mean (2011)	8.81	3.33	18.79	0.47	5.58	1408.23
Observations	6,971	6,971	6,971	6,971	6,971	6,971
Panel B: Child at Secondary level (aged 10-14 years)						
Treatment X 2009	10.071	-2.379	139.954***	0.297	15.143	-177.241*
	[35.065]	[37.303]	[26.099]	[10.692]	[26.857]	[101.357]
Treatment X 2011	6.970	-7.866	69.039**	-5.020	15.472	-76.098
	[34.078]	[30.645]	[29.755]	[7.141]	[30.916]	[123.822]
Constant	160.919***	137.803***	124.114***	-5.565	133.976***	563.318***
	[24.691]	[18.149]	[19.340]	[3.585]	[16.969]	[52.743]
Control Mean (2008)	112.81	93.83	71.70	18.60	16.92	1170.30
Control Mean (2011)	68.06	74.05	63.17	10.28	49.03	1444.24
Observations	5,570	5,570	5,570	5,570	5,570	5,570

Note: All the standard errors are cluster at the Branch level to estimate P-value. Sub-district level fixed effects are controlled in each regression. Standard errors are clustered at the branch level.

Table 4. Program impact on children working hours by sex (Yearly/hour)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Household Activity	Wage Work	Livestock	Agricultural Self-employment	Non-agricultural Self-employment	Study
Panel A: Boys						
Treatment X 2009	-3.572	-2.470	87.959***	9.092	-0.822	-168.399*
	[4.066]	[28.984]	[17.158]	[8.018]	[22.121]	[90.760]
Treatment X 2011	0.211	-8.296	46.419**	4.357	-2.565	-22.363
	[2.419]	[23.962]	[18.348]	[6.863]	[24.866]	[131.677]
Constant	9.972	143.332***	92.278***	-4.114	98.010***	566.073***
	[6.582]	[22.211]	[31.699]	[3.629]	[14.793]	[66.458]
Observations	6,502	6,502	6,502	6,502	6,502	6,502
Panel B: Girls						
Treatment X 2009	19.731	8.380	77.661***	1.330	0.843	-202.847**
	[30.619]	[6.807]	[20.379]	[3.257]	[11.316]	[90.644]
Treatment X 2011	14.674	0.075	55.754**	2.007	5.374	-55.986
	[30.673]	[8.387]	[25.285]	[3.252]	[14.525]	[147.534]
Constant	152.845***	8.262	97.821***	5.781*	20.675***	812.836***
	[22.830]	[5.523]	[13.824]	[3.061]	[3.811]	[70.755]
Observations	6,039	6,039	6,039	6,039	6,039	6,039

Note: All the standard errors are cluster at the Branch level to estimate P-value. Sub-district level fixed effects are controlled in each regression. Standard errors are clustered at the branch level.

Table 5. Program impact on the targeted female's working hours (Yearly/hour)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Household Activity	Wage Work	Livestock	Agricultural Self-employment	Non-agricultural Self-employment	Servant
Treatment X 2009	-85.606	-31.282	551.041***	17.100	-19.094	-66.190
	[110.056]	[51.885]	[50.648]	[14.164]	[18.032]	[42.870]
Treatment X 2011	54.893	-52.459	445.679***	28.778**	9.681	-125.192***
	[113.900]	[47.356]	[51.298]	[10.897]	[21.382]	[44.368]
Constant	1,148.419***	201.160***	340.355***	-1.332	40.018**	487.335***
	[77.401]	[29.154]	[23.988]	[3.598]	[16.207]	[93.972]
Control mean (2009)	1455.59	292.23	406.44	47.56	74.87	350.32
Control mean (2011)	1389.26	396.44	439.47	20.46	55.75	402.90
Observations	9,603	9,603	9,603	9,603	9,603	9,603

Note: All the standard errors are cluster at the Branch level to estimate P-value. Sub-district level fixed effects are controlled in each regression. Standard errors are clustered at the branch level.

Table 6. Program impact on other working aged member working hours (Yearly/hour)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Household Activity	Wage Work	Livestock	Agricultural Self-employment	Non-agricultural Self-employment	Study	Servant
Treatment X 2009	14.867	-86.995	182.226***	29.637	62.426**	-36.113*	1.992
	[17.042]	[66.433]	[18.509]	[18.135]	[26.004]	[18.125]	[27.505]
Treatment X 2011	21.304	-14.190	139.495***	62.093***	69.240**	-70.456**	1.127
	[18.881]	[76.115]	[25.835]	[22.545]	[31.711]	[31.923]	[29.007]
Constant	116.418***	1,051.632***	98.303***	83.327***	195.994***	28.340	54.230***
	[14.325]	[88.212]	[17.532]	[11.534]	[34.569]	[17.123]	[16.906]
Control mean (2009)	162.70	826.62	112.06	104.80	68.14	155.45	86.63
Control mean (2011)	156.70	789.91	126.30	77.52	158.70	275.68	86.57
Observations	11,157	11,157	11,157	11,157	11,157	11,157	11,157

Note: All the standard errors are cluster at the Branch level to estimate P-value. Sub-district level fixed effects are controlled in each regression. Standard errors are clustered at the branch level.

Table 7. Program impact on children working hours controlling livestock income (Yearly/hour)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All children		Primary level		Secondary level		Male		Female	
VARIABLES	Total effect	Net effect	Total effect	Net effect	Total effect	Net effect	Total effect	Net effect	Total effect	Net effect
Treatment X 2009	83.067***	64.461***	42.522***	33.222***	139.954***	115.225***	87.959***	70.049***	77.661***	57.524***
	[17.319]	[14.695]	[13.301]	[11.060]	[26.099]	[23.350]	[17.158]	[14.141]	[20.379]	[17.879]
Treatment X 2011	50.825**	32.763*	29.782*	19.253	69.039**	45.537*	46.419**	32.087**	55.754**	32.667
	[20.134]	[16.808]	[15.798]	[11.881]	[29.755]	[26.113]	[18.348]	[15.316]	[25.285]	[21.756]
Constant	95.035***	76.858***	51.859**	37.881***	124.114***	107.493***	92.278***	76.029***	97.821***	76.939***
	[21.926]	[13.073]	[21.801]	[13.661]	[19.340]	[13.866]	[31.699]	[21.729]	[13.824]	[9.169]
Observations	12,541	12,541	6,971	6,971	5,570	5,570	6,502	6,502	6,039	6,039

Note: All the standard errors are cluster at the Branch level to estimate P-value. Sub-district level fixed effects are controlled in each regression. Standard errors are clustered at the branch level.

Table 8. Program impact on children working hours controlling mobility of the targeted women (Yearly/hour)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All children		Primary level		Secondary level		Male		Female	
VARIABLES	Total effect	Net effect	Total effect	Net effect	Total effect	Net effect	Total effect	Net effect	Total effect	Net effect
Treatment X 2009	83.067***	188.585***	42.522***	63.372***	139.954***	278.231***	87.959***	147.377***	77.661***	227.666***
	[17.319]	[17.610]	[13.301]	[13.373]	[26.099]	[26.146]	[17.158]	[17.399]	[20.379]	[20.698]
Treatment X 2011	50.825**	117.524***	29.782*	90.884***	69.039**	140.805***	46.419**	87.795***	55.754**	148.000***
	[20.134]	[19.985]	[15.798]	[15.849]	[29.755]	[29.358]	[18.348]	[18.377]	[25.285]	[25.011]
Constant	95.035***	119.888***	51.859**	61.175***	124.114***	155.076***	92.278***	109.540***	97.821***	133.613***
	[21.926]	[20.884]	[21.801]	[21.693]	[19.340]	[17.944]	[31.699]	[29.733]	[13.824]	[13.762]
Observations	12,541	12,541	6,971	6,971	5,570	5,570	6,502	6,502	6,039	6,039

Note: All the standard errors are cluster at the Branch level to estimate P-value. Sub-district level fixed effects are controlled in each regression. Standard errors are clustered at the branch level.

Annex

Table A. First stage result for table 7

VARIABLES	All	Primary	Secondary	Boy	Girl
Treatment	-8.600	-6.616	-9.050	-5.792	-10.772
	[10.307]	[7.003]	[18.475]	[9.720]	[12.776]
2009	3.924	-1.903	6.838	-5.800	15.089
	[10.891]	[7.631]	[17.520]	[9.795]	[13.811]
2011	7.078	-0.986	0.486	3.800	11.643
	[12.003]	[7.888]	[19.345]	[12.108]	[14.612]
Treatment X 2009	64.461***	33.222***	115.225***	70.049***	57.524***
	[15.658]	[11.346]	[25.123]	[14.504]	[19.101]
Treatment X 2011	32.763*	19.253*	45.537*	32.087**	32.667
	[16.906]	[11.356]	[26.406]	[15.317]	[21.185]
Income	0.021**	0.026*	0.019*	0.027***	0.018*
	[0.009]	[0.013]	[0.010]	[0.005]	[0.011]
Treatment X Income	0.028***	0.027*	0.017	0.022***	0.031*
	[0.010]	[0.013]	[0.012]	[0.005]	[0.017]
Treatment X Income X 2009	-0.019***	-0.019***	-0.013	-0.022***	-0.015
	[0.005]	[0.005]	[0.009]	[0.004]	[0.015]
Treatment X Income X 2011	-0.028***	-0.024***	-0.018*	-0.031***	-0.024
	[0.005]	[0.006]	[0.009]	[0.006]	[0.014]
Constant	76.858***	37.881**	107.493***	76.029***	76.939***
	[13.801]	[14.247]	[14.413]	[22.372]	[9.717]
Sub-district fixed effect?	Yes	Yes	Yes	Yes	Yes
Observations	12,541	6,971	5,570	6,502	6,039
R-squared	0.188	0.259	0.166	0.196	0.193

Table B. First stage result for table 8

VARIABLES	All	Primary	Secondary	Boy	Girl
Treatment	-34.112	-17.980	-53.222	0.109	-71.244**
	[31.398]	[19.959]	[61.559]	[46.269]	[33.202]
2009	7.446	-0.619	12.544	-4.233	20.329
	[11.416]	[8.090]	[18.092]	[10.571]	[13.991]
2011	9.514	0.194	3.822	5.745	14.630
	[12.562]	[8.534]	[20.076]	[12.487]	[14.974]
Treatment X 2009	188.585***	63.372*	278.231***	147.377**	227.666***
	[42.751]	[34.578]	[76.944]	[62.176]	[51.532]
Treatment X 2011	117.524**	90.884***	140.805*	87.795	148.000***
	[44.698]	[33.398]	[78.113]	[54.056]	[50.910]
Mobility	-17.456***	-6.234*	-22.500**	-13.268**	-23.585**
	[5.433]	[3.329]	[8.514]	[6.557]	[9.594]
Treatment X Mobility	17.233	8.190	28.520	0.173	35.735**
	[15.402]	[8.223]	[32.101]	[22.935]	[16.542]
Treatment X Mobility X 2009	-56.551***	-11.098	-76.408*	-31.619	-80.647***
	[19.822]	[15.011]	[39.239]	[28.709]	[27.267]
Treatment X Mobility X 2011	-35.901*	-32.585**	-39.399	-22.154	-49.724**
	[19.939]	[12.248]	[38.730]	[25.482]	[22.574]
Constant	119.888***	61.175***	155.076***	109.540***	133.613***
	[22.288]	[22.411]	[23.122]	[31.607]	[22.715]
Sub-district fixed effect?	Yes	Yes	Yes	Yes	Yes
Observations	12,541	6,971	5,570	6,502	6,039
R-squared	0.061	0.045	0.089	0.058	0.075