The Short and Longer Term impacts of Asset Transfer on Child Labor: Evidence from a Randomized Experiment in Bangladesh

Abstract

Using longitudinal data from Randomized Controlled Trials, we estimate the effect of *asset transfer program* on nature of work of the beneficiary’s children aged 5 to 14 years using a triple differenced model. Our findings show that the likelihood of adopting entrepreneurship increases significantly among the children of participant households in the short, medium, and long run. The findings are driven by girls of participant households who are likely to devote more time on non-agricultural skilled employment in the longer run. It seems that this reduces their time to study in the short and long run, and reallocates their time away from distress jobs and substituting or complementing mother’s work. Heterogeneous impacts of gender of the household head, age and baseline occupations of the children are observed. Our findings confirm that grant recipient households are more likely to inject their children into the labor market as found in the literature.

Key words: Bangladesh, Child labor, Gender, Working hours, Asset transfer

# Introduction

Child labor refers to the engagement of children in any effort that takes away their childhood, impedes their opportunities to attend school, leading to economically and socially sub-optimal outcomes. The International Labor Organization (ILO) estimates that around 168 million children are in child labor in the 5-17 years age group of which 120 million are in child labor in the 5-14 years age; notably, the most significant absolute number of child laborers originate in the Asia Pacific region (ILO 2013). The World Bank (1998) accounts that the labor market involvement rate of 10 to 14 years children is highest, about 30–60 per cent, in countries with per capita income of $500 or less. Child labor is common in developing countries due to the consequence of poverty, vulnerability, and economic shocks (Landmann and Fr ̈olich, 2015; Bandara et al., 2015; Krueger, 1996; Fallon and Tzannatos, 1998; Edmonds, 2008; Beegle et al., 2006; Dillon, 2013; Duryea et al., 2007). Bangladesh is not exceptional; statistics show about 4.7 million children aged 5 to 14 in the workforce, which is about 12.6% of them.[[[1]](#footnote-1)](#_ftn1" \t "_blank) About 93 per cent of child laborers work in the informal sectors such as in small factories and workshops, on the street, in home-based businesses and domestic employment and alarmingly, these activities are mostly outside the purview of the labor laws. [[2]](#footnote-2)

Numerous studies show substantial adverse effects of child labor on academic achievement, school attendance, human capital accumulation (Gunnarsson et al., 2006; Beegle et al., 2005; Heady, 2003; Rosati and Rossi, 2003), adult incomes (Emerson and Souza, 2011; Kassouf et al., 2001; Ilahi et al., 2000), and potentially hazardous occupations and bad physical, intellectual, and mental health outcomes as an adult (Kassouf et al., 2001; Lee and Orazem, 2007; Radfar et al., 2018). Grace Abbott[[3]](#footnote-3) states, “child labor and poverty are inevitably bound together and if you continue to use the labor of children as the treatment for the social disease of poverty, you will have both poverty and child labor to the end of time”.

To reduce child labor and promote schooling, different social protection programs, such as conditional cash transfer program have been implemented around the world. Because, the incidence of school dropout at an earlier age is higher among the families having lower incomes, and less productive assets (Jacoby, 1994). Ravallion and Wodon (2000) find that the Food for Education Program (FEE) in Bangladesh increases school attendance with a little decrease in child labor. Similar findings observe by Schultz (2004), and Miller and Tsoka (2012) from randomized experiment data of the Mexican Progresa poverty program and Malawi cash transfer program, respectively. However, the conditional cash transfer program in Nicaragua influences on the volume and quality of child labor, specifically, the program has trimmed down child labor for household chores and traditional farming whereas improved it for non-traditional work related to business and retail (Del Carpio et al., 2016). De hoop and Rosati (2014) find decrease working hours for boys in economic activities while for girls such decreases in household chores. Maluccio and Flores (2005) in Nicaragua, Skoufias and Parker (2001) in Mexico, and Filmer and Schady (2009) in Combodia find reduction of work among children. Borraz and González (2009) observe a reduction in female child labor in Montevideo, but no impact on school attendance. Cardoso and Souza (2004) find an increase of student enrolment in Brazil with no differences in child labor that corresponds to the study conducted by Attanasio et al. (2010), Glewwe and Olinto (2004). Bauchet et al. (2018) find a negative impact on school enrolment in Bolivia while Amarante et al. (2011) find no effect on school attendance, child labor, or household income in Uruguay. However, Pais et al. (2017) observe that the program increases child labor in Brazil.

Though the conditional cash transfer program aims to invest in children’s human capital (Fiszbein et al., 2009), the program is not effective enough to reduce child labor may be due to small transfers which are not adequate to skip the labor (Cardoso and Souza, 2004). Schultz (2004) confirms this argument by mentioning that most of the time, child labor earnings are higher than the benefits. Moreover, the short duration and lower amount of grant are not enough to make children attending school, and that is why the children are driven to workplaces (Lee and Hwang, 2016). Several studies show positive effects of cash and asset transfers programs on income, employment of the adult member, food security, food consumption, productive assets, psychological status, accessing and using of health services, and school enrolment of the children (Gobin et al., 2017; Barrientos and DeJong, 2004; Social Protection Advisory Service, 2003; Bandiera et al., 2016; Krishna et al., 2012; Hulme and Moore, 2007; Emran et al., 2014; Bauchet et al., 2015, Bauchet et al., 2018; Banerjee et al., 2015). Few studies assess the impact of a randomized asset transfer program on child labor. Sulaiman (2015) finds a short term effect of the asset transfer program on children’s education expenses and working hour on livestock rearing, but no effect on school enrolment. Bandiera et al. (2016) also find a positive impact of the same program on children working hour on livestock rearing and land cultivation.

Observing these mixed results, it is worth noting that low-income families are likely to send the kids for work parallel to schooling to meet up their family needs. It is imperative to look at whether the transfer programs that target the main female of the households for their financial upliftment affects the volume and nature of work the children are involved in.  No effort has been made to explore whether the grant-based asset transfer program affects the nature of work of the ultra-poor children in the long run other than households financial improvement. Thus, this study explores the effectiveness of such a program on (1) the nature of work of the children, (2) the volume of child labor within households, and (3) whether this varies with gender. Using four rounds of panel data, this study estimates the effectiveness of BRAC’s anti-poverty program titled “Targeting the Ultra-Poor (TUP)” program[[4]](#footnote-4) implemented in Bangladesh where Randomized Controlled Trial has been adopted in the implementation design. Considering the heterogeneity among the ultra-poor, the TUP program implements two intervention packages: (1) Specially Targeted Ultra-poor package (referred to as STUP package), a grant-based support package that transfers asset as grant, and (2) Other Targeted Ultra-poor package (referred to as OTUP package) that provides soft loan[[5]](#footnote-5). The STUP package includes asset transfer (mostly livestock and poultry), training on income-generating activities, weekly stipends, health support, etc. The STUP package generally targets the ultra-poor who are relatively more vulnerable than those targeted by the OTUP package. This study focuses on the STUP support package and contributes to the literature by providing insights on how it affects the nature of work of the children and time allocation of child labor, which is represented by their time spent on work.

Findings show that the likelihood of adopting agri- and non-agricultural self-employment increases significantly over the year among the children of program participant households. Female children in the same households are likely to devote significantly more time on non-agricultural skilled employment in the longer run. Evidence shows that children of male-headed program participant households are likely to spend significantly less time on agricultural self-employment in the short and long run while dedicating significantly more time on non-agricultural skilled employment in the longer run. Our findings correspond to the studies where authors claim that the eligible grant recipient households are more likely to inject their children into the labor market.

The remainder of the paper is organized as follows. In Section 2, we describe the TUP program. Section 3 and section 4 describe the conceptual framework on how asset transfer program affects child labor, and experimental design, respectively. In Section 5, we present the short-medium- and longer-run results of the evaluation. Section 6 offers conclusions.

# Overview of the TUP program

The TUP program implements an innovate ‘Graduation’ approach that combines the components of livelihoods, social safety nets, financial inclusion and social integration for two years where each of this component grabs distinct parts of extreme poverty.[[6]](#footnote-6) Multidimensional supports that include subsistence allowance, asset transfers, life skills and technical skills training, community mobilisation and health care support, coaching on positive behaviour change, and savings opportunities to meet immediate needs of the participants are provided under the program (Figure 1). However, conventional development programs are not able to cope up with these multidimensional needs.



**Fig. 1.** Graduation approach

 Source: TUP program[[7]](#footnote-7)

The program was first piloted in three northern districts of Bangladesh in 2002 and then scaled up across the country. Around 100,000 ultra-poor households from rural areas of Bangladesh were covered in its first phase (2002-2006) of implementation. Productive assets such as livestock and poultry along with a daily allowance, training, and some other kinds of support were provided as grants. Overtime, based on programmatic and in-house research learning, BRAC incorporated diversity in program support, and introduced the STUP and OTUP support packages in phase II (2007-2011)[[8]](#footnote-8) and subsequent cohorts of the program. The selection procedure of the eligible households and their support packages are described below.

## *Selection procedure*

The program follows a three-step procedure to select the ultra-poor. Initially, based on the poverty mapping of the World Food Program, the poorest sub-districts are identified (BBS and WFP, 2004). From the selected sub-districts, communities that have a high concentration of poverty are identified based on the own knowledge of the TUP program staff or discussion with the staff of other BRAC programs (microfinance, health, education, so forth). In the selected villages, a participatory Rural Appraisal (PRA) exercise (Chambers, 1994) is carried out at the beginning. The PRA starts with a village-level meeting, and a large map of the village is drawn during the process. All the households and landmarks in the village are identified to capture all the households including those who are invisible households or families that residing within others’ homes like on their balconies or even mobile. After identifying all the households, communities are divided into clusters of 80-120 households and carried out the wealth ranking exercise. All the identified households in each community are ranked into 5-6 wealth groups (e.g., very poor, poor, lower middle-class, upper middle class, and non-poor). Afterwards, households from the bottom three wealth groups are visited and verified by the program staff to select households eligible for STUP and OTUP support packages based on the selection criteria specified by the program. The program targets those who have little or no land or productive assets and simultaneously struggle to cope up with the dearth of basic security and entitlement including that of food security, public health, and social honor. Most of the cases, they are being excluded from social services and healthcare, and are often unable to work due to chronic sicknesses or disability in the family.

The selection criteria[[9]](#footnote-9) of STUP support package includes (i) household owns less than 10 decimals of land, (ii) children of school going age (5-14 years) are engaged in income-generating activities, (iii) household has no productive assets, (iv) household is mainly dependent on irregular earning (from working as a housemaid, day laborer, begging etc.) of female members, and (v) has no male members capable of working. During verification, female-headed households where the main women are widow, divorced, or separated are given special efforts to ensure their active participation.

In addition to the inclusion criteria discussed above, the program uses two exclusion criteria: (1) households with no adult women capable of working are excluded as the program provides support only to women[[10]](#footnote-10); and (2) participants of microfinance and/or recipients of Government/NGO support are excluded to avoid duplications. A household must meet at least three of the above mentioned five inclusion criteria and none of the exclusion criteria to be eligible for the STUP support package.

## *Support package*

Once the selections are made, program provides the eligible STUP households[[11]](#footnote-11) with: (1) enterprise development and life skill training; (2) asset - mostly livestock and poultry with an average value of USD 140 which is one-shot transfer; (3) a weekly subsistence allowance (around USD 2.6) during the first 36-40 weeks to compensate for any income losses that might occur due to the eligible woman’s occupational change; (4) health subsidies (BRAC bears health expenses for the household members and provides micronutrient sachets); and (5) community mobilization support. The participants are initially provided with hands-on training on income-generating activities such as cow/goat rearing and cow fattening, after which the participants receive the assets. The program delivers enterprise development training to the participants so that they can properly utilize the transferred assets. Close supervision[[12]](#footnote-12) of the participant in individual and group settings is also provided through the front line staff[[13]](#footnote-13) on their economic growth and health conditions that enables the participants to develop sustainable livelihoods because regular monitoring support motivates the participants’ to work, improves their entrepreneurial skills, and builds up their confidence to make decisions. Weekly home visits for providing continuous coaching on general awareness about social and health issues[[14]](#footnote-14) and positive behavior change continue for two years as well. Additionally, monthly or bi-monthly visits of livestock specialists continue for the first year. BRAC also provides them with some additional inputs, such as fodder for cattle.

# How can *asset transfer program* affect child labor?

The *asset transfer program* provides asset to the main female of the households for their financial upliftment. Thus, the program mainly focuses on economic aspects of the beneficiaries, such as how the asset could be expanded, how new income sources can be generated, how to manage the daily income, etc. For that, the program provides some support services through the Program Organizers (PO) who consistently push them to invest their income to productive sectors like leasing in land for cultivation or starting up a new business to diversify income opportunities. As already mentioned that several studies show the success of the program in those economic aspects. Moreover, as school attendance is not a direct component of the *asset transfer program*, in this study, we will not focus on that. This study focuses on whether this financial improvement has any effect on time allocation of child labor among the children of grant recipient mother. We are not too ambitious to assume that financial improvement would disappear child labor. Thus, we expect that it would improve their nature of work as mixed effects of the conditional cash and asset transfer program observe on child labor in several studies.

Family’s improved socioeconomic conditions help children’s development that contributes to ending child labor (Pais et al., 2017). Bandara et al. (2015) find that an increase in the family’s access to credit and assets reduce the child’s time allocation on paid or unpaid work. However, evidence shows that health insurance reduces economic vulnerability, and that significantly decreases child labor on risky work and earnings in Pakistan (Landmann and Fr ̈olich, 2015). While Beegle et al. (2006; 2003) show that the prevalence of using child labor is higher among the credit-constrained households to smooth their income, and household’s access to credit in response to crop shocks are likely to reduce child labor and increase household welfare.

On the other hand, several authors claim that increasing household access to credit market leads to reduction or delayed school enrolment, and coincidental consequences of child labor (Lakdawala, 2018[[15]](#footnote-15); Wydick, 1999; Menon, 2004; Shimamura and Lastarria-Cornhiel 2010; Augsburg et al., 2012). Increased access to financial market improves food security and enables the households to start up new business activities that prefer child labor considering future income fluctuations, and therefore education becomes less important (Fumagalli and Martin, n.d.). Becker (1962) mentions that younger human capitals are more desirable for long run investment. According to Edmonds and Theoharides (2018) “a successful productive asset grant could reduce child labor via a wealth effect if child labor markets are complete, but with incomplete markets, the value of child time will also be impacted”. Because imperfect labor and financial markets, fluctuations in seasonal earnings, and sudden shocks affect schooling (Jacoby and Skoufias 1997; Edmonds et al., 2010); these lead to an increase in child labor (Ranjan, 2001; Beegle et al., 2003; Beegle et al., 2005; Dillon, 2008). However, according to Edmonds (2008) “the relationship between child labor and female power in the household is predicted to be a U-shape”. This is again examined by Ray and Basu (2002) in Nepal and indicates that when the power of a woman increases, it leads to preliminary fall of child labor, but beyond a point, it leads to increase again.

Thus, we assume that increased asset and income of the TUP beneficiaries may affect their children in two ways: firstly, it would keep the children away from distress occupation[[16]](#footnote-16), and secondly, the children would be used to substitute or complement mother’s work. However, no study focused on the volume and nature of work of the children of ultra-poor households where mother receives a grant under the *asset transfer program* of TUP in the longer run.

# Experimental design

## *Data*

This study uses four rounds of panel data of BRAC’s TUP program collected in 2007, 2009, 2011, and 2014.[[17]](#footnote-17) This is the second phase[[18]](#footnote-18) of the TUP program, and we choose this cohort as a Randomized Controlled Trial (RCT) has been adopted in the implementation of the program. Data were collected from 20 sub-districts that cover 13 poorest districts in Bangladesh.[[19]](#footnote-19) Within each sub-district, further geographical selection was carried out in discussion with the field-level BRAC staff and identified at least two branches[[20]](#footnote-20) of which each was randomly assigned as treated or control branch[[21]](#footnote-21). Therefore, the survey was conducted in 40 branches (20 treatment and 20 control branches) and 1309 communities. The average distance between treatment and control branch is around 12 km. Communities within the same sub-district are subject to the same local governance structures, and experience similar local policies. To minimize the risk of contamination between treatment and control units, branches rather than communities were used as the unit of randomization. Though the survey includes three groups of households from the wealth ranking in each location: (i) the ultra-poor, (ii) the other-poor who are primarily selected during the PRA but later eliminated during the verification, and (iii) the non-poor, this study focuses on only the ultra-poor group who are eligible for the STUP support package.

At baseline, 7,953 eligible households were surveyed, and the attrition rate is about 22% after seven years of intervention.[[22]](#footnote-22) Using the same but three years panel data, Bandiera et al. (2016) show that the attrition rate was 15 per cent after four years of intervention and that does not vary among treatment and control groups.

As mentioned, the RCT technique was followed in designing the study, but that is not intact fully anymore. After the second follow up survey in 2011, the TUP program provides support to some of the ultra-poor households in the control branches as well. In total, 495 households have received the TUP program support after 2011 in the control areas, and we exclude these households from our analysis. As a substantial number of households are still unaffected in the control group, the longer term effects of TUP on child labor is carried out using four rounds pooled panel data that includes only those households where the same main female respondents were surveyed in all the waves[[23]](#footnote-23) and the respondents have at least one child age 5-14 years. Therefore, we measure the impact of the TUP program on child labor on only the finally selected respondents’ kids[[24]](#footnote-24) – the average treatment effect on the treated (ATT). So, the households among the treated communities who were primarily selected but not received program support are eventually eliminated. The primary respondent was the main female member of the household.

Further, we conduct power calculation (to check whether we have enough sample to achieve minimum effect size) based on one-sided hypothesis tests about detecting a decline in child labor rather than the two-sided hypothesis testing that is more standard. We follow convention in the social sciences for power calculations, using a significance level (probability of Type I error) of 0.05 and power (probability of avoiding a Type II error) of 0.8. We assumed a one-sided test and an intra-cluster correlation of 0.2 consistent with estimates that have been used in the literature on RCTs in the educational sector (Hedges and Hedberg, 2007; Edmonds and Theoharides, 2018). About 13.6 per cent of children in Bangladesh were engaged in hazardous forms of child labor in 2007, and we anticipate a 30 per cent decline[[25]](#footnote-25) in the prevalence of hazardous child labor implying a sample of 480 children from 40 branches, 12 children per branch. Our sample is larger than 480 children in all the waves.

## *Estimation model*

Using experimental panel data, this study assesses the impact of the *asset transfer program* of TUP on time allocation of child labor in the longer run. The randomized assignment of a large sample of eligible households to treatment and control groups would help to ensure that observable and unobservable characteristics of the households are likely balanced across the two groups at baseline. Therefore, any differences between the treatment and control households at follow-up that is in the short (after two years of intervention) and long run (after four or seven years of intervention) could then be interpreted as causal impacts of the program. To evaluate the effect of the interventionon child labor, we compare daily working hours of the children of program participant versus non-participant households using the difference-in-difference technique. We estimate the following linear difference-in-differences model for each outcome $y\_{idtj}$ of child $i$ measured in subdistrict $d$ at time t (2007 baseline (t=0) and followed up in 2009, 2011, 2014 (t=1)) and occupation j (j=household chores, student, agricultural self-employment, non-agricultural skilled work, and unskilled work):

$y\_{idtj}=α+β\_{1}P\_{idj}+β\_{2}T\_{t}+δ(T\_{t}\*P\_{idj})+λX\_{i0}+γ\_{d}+ϵ\_{idt}$… … … … (1)

Where $P\_{idj}$ is a dummy variable denoting child of program participant household $i$ lives in treated communities. T denotes survey waves and the parameter $δ$ is the double-difference estimator of the average program effect. X represents a vector of children’s age, mother’s and household characteristics at baseline (i.e., in 2007); $γ\_{d}$ are subdistrict fixed effects that capture geographical heterogeneity. Despite randomization, our models control for demographic characteristics such as age of the child, sex of the household head, household size; and socioeconomic characteristics such as education and employment status of the mother/respondent, per capita income, ownership of land, livestock and savings, to justify any compositional differences in the sampled children of ultra-poor households. De Carvalho Filho (2012) suggests that though the program intervention can be an important instrument to reduce child labor, regional and gender factors are also other critical determining factors of child labor relative to poverty. Summary statistics of control variables are presented at Annex Table A1. We control for baseline characteristics, rather than time-varying household characteristics as these could potentially be affected by the intervention. We use individual fixed effects model to control for the many observed and unobserved individual characteristics that could affect child labor. Standard errors are adjusted for clustering at the individual level. Model 1 allows us to identify the causal impact of the TUP on the outcomes of interest. For each of the outcomes, we present impact estimates for all children combined and stratified by age and gender to show the precise effects for different groups.

This study focuses on the working hours of the respondents’ children aged 5 to 14 years. We classify the various employment choices into five categories: household chores, student, agricultural self-employment (cultivation, livestock rearing, fishing, vegetable gardening, and nursery), non-agricultural skilled employment (skilled carpenters, skilled blacksmiths, garments workers, health workers, tailoring, handicrafts, and small business); and unskilled employment (agricultural or non-agricultural day laborer, work as maids/servants).

We hypothesize the TUP to have a heterogeneous impact on child labor across three dimensions: (i) gender of the household head (ii) age of the children, and (iii) baseline occupations. Firstly, we hypothesize the effects of TUP on time allocation of child labor to vary across gender of the household head for several reasons. Gender of the household head is an essential factor to determine child labor as De Carvalho Filho (2012) mentions that children of female-headed households are more likely to work and are less likely to attend school. The earlier model shows the impact of the program on the working hours of the respondents’ kids aged 5 to 14 years. Therefore, to measure the heterogeneous impact of TUP on child labor across the gender of the household head, we use the following difference-in-difference with triple interaction model. If we would estimate difference-in-difference to explore whether child labor is higher among the male-headed household compared to the female-headed households, we would miss out the impact of the program. Thus, Model 2 allows us to identify the causal impact of TUP on the outcomes of interest. We estimate the following triple interaction model for each outcome $y\_{idtj}$ of child i measured in subdistrict $d$ at time t (2007 baseline (t=0) and followed up in 2009, 2011, 2014 (t=1)) and occupation j (j=household chores, student, agricultural self-employment, non-agricultural skilled work, and unskilled work):

$y\_{idtj}=α+β\_{1}P\_{idj}+β\_{2}T\_{t}+β\_{3}G+δ(T\_{t}\*P\_{idj}\*G)+λX\_{i0}+γ\_{i}+ϵ\_{idt} $……….. (2)

Where, $G$ is a dummy variable denoting household head is male. The parameter $δ$ is the double-difference estimator with triple interaction of the average effect of the program.

Secondly, we hypothesize whether the child labor scenario is more pronounced among older children (11 to 14 years) compared to younger children (5 to 10 years). Similar to the previous model, we estimate the following triple difference model (Model 3) to identify the causal impact of TUP.

$y\_{idtj}=α+β\_{1}P\_{idj}+β\_{2}T\_{t}+β\_{3}A+δ(T\_{t}\*P\_{idj}\*A)+λX\_{i0}+γ\_{i}+ϵ\_{idt} $….. (3)

Here $A$ is a dummy variable denoting children age 11 to 14 years. The parameter $δ$ is the double-difference estimator with triple interaction of the average effect of the program, whether child labor more pronounced among the older.

Thirdly, we hypothesize that children of program participant households who were involved in skilled or unskilled work at baseline will, therefore, be more likely to remain in or shift to skilled works in the long run. As studies show that grant recipient women shift to more entrepreneurial activities in the short, medium, and longer term (Bandiera et al., 2016), we assume that it would affect the children engaging in a better occupation like skilled self-employment rather than unskilled work like day laboring, maid, begging, etc. To assess the impact of the program on time allocation of child labor by baseline employment, we estimate the regression models separately for each subgroup.

# Preliminary findings and discussion

This section presents the findings of the different dimensions of the impacts as depicted in Section 4.

## *Impact on working hours of the children age 5-14 years*

Table 1 shows the impact of the *asset transfer program* on employment trajectories of the 5 to 14 years children estimated using model (1) for each of the survey year from the pooled panel. Looking at the results from the pooled panel, we find that the likelihood of adopting entrepreneurship increases significantly over the year. Results indicate (Panel A of Table 1) that average working hours of the children of TUP households are likely to increase significantly to agricultural self-employment (p<0.01) by 0.22 standard deviations in the short (2007-2009), 0.13 standard deviations in the medium (2007-2011) and 0.09 standard deviations in the long run (2007-2014). While children of program participant households are likely to spend significantly less time on study in the short and long run, no significant impacts observe on households chores, non-agricultural skilled and unskilled works. As mentioned earlier, several authors claim that increasing household access to credit market leads to reduction or delayed school enrolment, and coincidental consequences of child labor (Lakdawala, 2018; Wydick, 1999; Menon, 2004; Shimamura and Lastarria-Cornhiel 2010; Augsburg et al., 2012). According to Fumagalli and Martin (n.d.), “parents from poor households often face a difficult decision as to whether to send their children to school, given the strong trade-off between expected future returns to education and present wages”.

Gender disaggregated results show that these findings are driven by girls of participant households as their time to agricultural self-employment increases significantly by 0.21, 0.15, and 0.10 standard deviations in the short, medium, and long run, respectively (p<0.01). Interestingly, female children of the participant households are likely to devote significantly more time (0.08 standard deviations ahead) on non-agricultural self-employment in the longer run (p<0.10). It seems that this reduces their time to study in the short and long run, especially among 10 to 14 years girls of participant households. Findings show that average daily study time of the girls in the participant households reduces significantly by 0.65 standard deviations in the short (p<0.01), 0.22 standard deviations in the medium (p<0.10) and longer term (p<0.10). However, for unskilled work, no significant difference observes on time allocation of child labor among the girls of program participant and non-participant households. For working hours of boys, we find almost the same trends. However, age disaggregated result (Panel B and Panel C of Table 1) shows almost the same trends except 5 to 10 years boys are likely to shift more to unskilled work in the longer run (p<0.05). This may be due to the fact that boys are not getting the opportunity to involve in better occupation. Several studies find a gender gap in child labor and show that girls are more likely to engage in unsafe and risky occupation and take substantial burdens of works compare to boys (Blunch and Verner, 2001; Heady, 2003; Gautam and Sarangi, 2008). Though we do not find any significant difference between boys and girls of treated and control households on working hours in different occupations, our results show that girls of the treated households are more likely to involve in better occupation compare to the girls of the control counterparts.

To look at the heterogeneous impact of TUP on time allocation of child labor, we explore the impact of TUP on child labor across gender of the household head using triple interaction model 2. As can be seen from Table 2, results have changed dramatically when we explore the impact of the program across gender of the household head. Panel A of Table 2 shows no significant difference among the children of male-headed program participant and female-headed non-participant households on time devoted to household chores and study. However, average working hours of the children of male-headed program participant households are likely to reduce significantly on agricultural self-employment by 0.20 standard deviations in the short (p<0.01), and 0.11 standard deviations in the longer run (p<0.10). Notably, children of male-headed program participant households are likely to 0.41 standard deviations ahead to non-agricultural self-employment i.e., on skilled employment in the longer run (p<0.05) against the children of female-headed non-participant households. While, the average working hours of the children of male-headed program participant households are likely to reduce significantly by 0.43 standard deviations on unskilled work in the longer run (p<0.05). Gender disaggregated results are also showing almost the same trend where female children of male-headed program participant households are likely to spend on average 0.47 and 0.52 standard deviations less hours on unskilled work in the short and long run compared to the female-headed non-participant households. Boys of male-headed program participant households are likely to 0.53 standard deviations ahead to non-agricultural self-employment in the longer run (p<0.10) in comparison to the boys of the female-headed non-participant households.

Age disaggregated result (Panel B and Panel C of Table 2) shows almost the same trends. The primary school age children (age 5 to 10 years) of male-headed program participant households are likely to spend more time on non-agricultural self-employment, and less time in agricultural self-employment and unskilled works against the children of female-headed non-participant households. These findings pronounce more among the primary school age boys (5 to 10 years) and secondary school age girls (11 to 14 years).

It is well known that the male-headed households are comparatively less vulnerable than the female-headed ones, and our results also show the same. Children of male-headed households are likely to spend more time on non-agricultural skilled works and less time on agricultural and unskilled works. And these results are significantly pronounced among the children of program participant households against non-participants.

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| **Table 1** |  |  |
| Impact on daily working hours of the children age 5 to 14 year |  |
|  | Both | Girls | Boys |
| Panel A: 5 to 14 years | HH chores | Student | Agri-self work | Non agri-skilled work | Unskilled work | HH chores | Student | Agri-self work | Non agri-skilled work | Unskilled work | HH chores | Student | Agri- self work | Non agri-skilled work | Unskilled work |
| Impact after two years  | -0.007 | -0.543\*\*\* | 0.220\*\*\* | -0.073 | 0.053 | -0.003 | -0.645\*\*\* | 0.212\*\*\* | 0.006 | -0.016 | -0.002 | -0.450\*\*\* | 0.227\*\*\* | -0.153 | 0.122 |
| of intervention | (0.028) | (0.082) | (0.024) | (0.056) | (0.071) | (0.057) | (0.118) | (0.030) | (0.046) | (0.105) | (0.007) | (0.113) | (0.038) | (0.098) | (0.097) |
| Impact after four years  | -0.006 | -0.109 | 0.127\*\*\* | -0.014 | -0.009 | 0.017 | -0.222\* | 0.147\*\*\* | 0.062 | -0.134 | -0.013 | -0.001 | 0.111\*\*\* | -0.106 | 0.116 |
| of intervention | (0.028) | (0.093) | (0.024) | (0.059) | (0.076) | (0.054) | (0.133) | (0.031) | (0.042) | (0.110) | (0.015) | (0.130) | (0.037) | (0.104) | (0.103) |
| Impact after seven years  | -0.028 | -0.163\*\* | 0.093\*\*\* | 0.049 | 0.093 | -0.021 | -0.217\* | 0.097\*\*\* | 0.082\* | 0.059 | -0.006 | -0.092 | 0.089\*\* | -0.018 | 0.127 |
| of intervention | (0.028) | (0.079) | (0.023) | (0.056) | (0.071) | (0.056) | (0.111) | (0.031) | (0.049) | (0.105) | (0.008) | (0.111) | (0.035) | (0.097) | (0.096) |
| Control mean at baseline | 0.237 | 3.491 | 0.220 | 1.206 | 1.275 | 0.59 | 3.104 | 0.120 | 0.51 | 1.378 | 0.029 | 3.773 | 0.316 | 1.810 | 1.113 |
| Observations | 13878 | 13878 | 13878 | 13878 | 13878 | 6629 | 6629 | 6629 | 6629 | 6629 | 7249 | 7249 | 7249 | 7249 | 7249 |
| R-sq | 0.043 | 0.120 | 0.088 | 0.055 | 0.068 | 0.101 | 0.140 | 0.116 | 0.038 | 0.062 | 0.007 | 0.124 | 0.078 | 0.085 | 0.095 |
| Panel B: 5 to 10 years |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Impact after two years  | 0.007 | -0.548\*\*\* | 0.118\*\*\* | -0.032 | 0.027 | 0.025 | -0.566\*\*\* | 0.109\*\*\* | 0.001 | -0.023 | -0.004 | -0.535\*\*\* | 0.130\*\*\* | -0.069 | 0.080 |
| of intervention | (0.019) | (0.089) | (0.019) | (0.028) | (0.058) | (0.040) | (0.131) | (0.025) | (0.004) | (0.101) | (0.006) | (0.125) | (0.029) | (0.057) | (0.064) |
| Impact after four years  | -0.002 | 0.082 | 0.079\*\*\* | -0.025 | 0.031 | 0.037 | 0.074 | 0.071\*\* | 0.006 | 0.018 | -0.030 | 0.079 | 0.085\*\* | -0.064 | 0.048 |
| of intervention | (0.023) | (0.107) | (0.023) | (0.034) | (0.056) | (0.040) | (0.157) | (0.030) | (0.008) | (0.098) | (0.028) | (0.147) | (0.033) | (0.067) | (0.060) |
| Impact after seven years  | 0.002 | -0.080 | 0.036\* | -0.018 | 0.063 | 0.026 | -0.026 | 0.025 | -0.006 | -0.003 | -0.011 | -0.146 | 0.049 | -0.037 | 0.127\*\* |
| of intervention | (0.019) | (0.083) | (0.022) | (0.027) | (0.056) | (0.038) | (0.123) | (0.031) | (0.006) | (0.101) | (0.009) | (0.113) | (0.031) | (0.053) | (0.053) |
| Control mean at baseline | 0.066 | 1.414 | 0.093 | 0.293 | 0.672 | 0.155 | 1.434 | 0.042 | 0.015 | 0.951 | 0.030 | 1.366 | 0.140 | 0.591 | 0.397 |
| Observations | 7720 | 7720 | 7720 | 7720 | 7720 | 3790 | 3790 | 3790 | 3790 | 3790 | 3930 | 3930 | 3930 | 3930 | 3930 |
| R-sq | 0.013 | 0.188 | 0.044 | 0.017 | 0.028 | 0.031 | 0.180 | 0.062 | 0.022 | 0.042 | 0.010 | 0.205 | 0.043 | 0.034 | 0.038 |
| Panel C: 11 to 14 years |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Impact after two years  | -0.035 | -0.568\*\*\* | 0.366\*\*\* | -0.121 | 0.102 | -0.033 | -0.727\*\*\* | 0.371\*\*\* | 0.019 | -0.097 | -0.003 | -0.399\* | 0.346\*\*\* | -0.271 | 0.236 |
| of intervention | (0.068) | (0.152) | (0.053) | (0.143) | (0.174) | (0.137) | (0.226) | (0.066) | (0.120) | (0.240) | (0.018) | (0.206) | (0.082) | (0.245) | (0.248) |
| Impact after four years  | -0.025 | -0.338\*\* | 0.175\*\*\* | 0.006 | -0.015 | -0.016 | -0.492\*\* | 0.216\*\*\* | 0.128 | -0.351 | -0.001 | -0.213 | 0.136\* | -0.143 | 0.306 |
| of intervention | (0.065) | (0.163) | (0.048) | (0.138) | (0.174) | (0.127) | (0.234) | (0.062) | (0.106) | (0.242) | (0.019) | (0.223) | (0.076) | (0.241) | (0.245) |
| Impact after seven years  | -0.080 | -0.257\* | 0.149\*\*\* | 0.116 | 0.129 | -0.114 | -0.390\* | 0.162\*\*\* | 0.200 | 0.073 | -0.004 | -0.175 | 0.129\* | 0.002 | 0.257 |
| of intervention | (0.065) | (0.145) | (0.047) | (0.136) | (0.164) | (0.125) | (0.205) | (0.059) | (0.122) | (0.220) | (0.018) | (0.200) | (0.075) | (0.235) | (0.238) |
| Control mean at baseline | 0.538 | 8.702 | 0.511 | 3.33 | 2.726 | 1.651 | 6.882 | 0.413 | 1.339 | 1.960 | 0.059 | 9.818 | 0.628 | 4.602 | -.107 |
| Control baseline characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control sub-districts  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effects  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6158 | 6158 | 6158 | 6158 | 6158 | 2839 | 2839 | 2839 | 2839 | 2839 | 3319 | 3319 | 3319 | 3319 | 3319 |
| R-sq | 0.032 | 0.186 | 0.074 | 0.048 | 0.070 | 0.072 | 0.202 | 0.108 | 0.052 | 0.074 | 0.020 | 0.207 | 0.068 | 0.072 | 0.101 |
| Notes: \*\*\*, \*\*, and \* denote significant at 1%, 5%, and 10% level respectively. Average treatment effect on the treated (ATT) estimates are reported based on a difference-in-difference specification estimated using OLS. The coefficients shown are those on the treatment-survey wave interaction terms. Each coefficient corresponds to a separate regression. The sample includes individuals in the same household as a child of the grant recipient ultra-poor woman. Standard errors are clustered at the individual level. All outcomes are measured at the individual level.  |

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| --- | --- | --- | --- | --- |
| Table 2 |  |  |  |  |
| Impact on per day working hours of the children of male-headed households  |  |  |  |
|  | Both | Girls | Boys |  |  |
| Panel A: 5 to 14 years | HH chores | Student | Agri-self work | Non agri-skilled work | Unskilled work | HH chores | Student | Agri-self work | Non agri-skilled work | Unskilled work | HH chores | Student | Agri-self work | Non agri-skilled work | Unskilled work |
| Impact after two years  | 0.051 | -0.099 | -0.201\*\*\* | 0.126 | -0.047 | 0.082 | -0.065 | -0.264\*\*\* | 0.063 | -0.469\* | 0.033 | -0.110 | -0.135 | 0.179 | 0.318 |
| of intervention | (0.076) | (0.201) | (0.067) | (0.166) | (0.190) | (0.153) | (0.294) | (0.089) | (0.120) | (0.265) | (0.021) | (0.277) | (0.097) | (0.292) | (0.267) |
| Impact after four years  | 0.098 | 0.214 | -0.082 | 0.041 | -0.130 | 0.125 | 0.0376 | -0.089 | 0.172 | -0.207 | 0.086 | 0.466 | -0.070 | -0.083 | -0.096 |
| of intervention | (0.087) | (0.254) | (0.069) | (0.182) | (0.213) | (0.167) | (0.359) | (0.099) | (0.105) | (0.316) | (0.061) | (0.351) | (0.096) | (0.316) | (0.287) |
| Impact after seven years  | 0.035 | 0.0928 | -0.114\* | 0.410\*\* | -0.430\*\* | 0.111 | 0.0276 | -0.154 | 0.175 | -0.524\* | 0.043 | 0.272 | -0.075 | 0.530\* | -0.428 |
| of intervention | (0.087) | (0.208) | (0.06) | (0.174) | (0.204) | (0.172) | (0.293) | (0.09) | (0.115) | (0.295) | (0.027) | (0.292) | (0.092) | (0.302) | (0.280) |
| Control mean at baseline | 0.219 | 3.392 | 0.248 | 1.264 | 1.146 | 0.545 | 2.919 | 0.150 | 0.559 | 1.107 | 0.016 | 3.712 | 0.348 | 1.860 | 1.087 |
| Observations | 13878 | 13878 | 13878 | 13878 | 13878 | 6629 | 6629 | 6629 | 6629 | 6629 | 7249 | 7249 | 7249 | 7249 | 7249 |
| R-sq | 0.044 | 0.121 | 0.091 | 0.057 | 0.070 | 0.102 | 0.141 | 0.120 | 0.040 | 0.064 | 0.013 | 0.125 | 0.080 | 0.087 | 0.098 |
| Panel B: 5 to 10 years |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Impact after two years  | -0.050 | -0.476\*\* | -0.151\*\* | 0.281\*\*\* | -0.165 | -0.109 | -0.156 | -0.201\*\* | 0.004 | -0.445 | 0.007 | -0.780\*\* | -0.087 | 0.522\*\* | 0.114 |
| of intervention | (0.058) | (0.240) | (0.068) | (0.107) | (0.189) | (0.124) | (0.354) | (0.089) | (0.008) | (0.291) | (0.013) | (0.325) | (0.094) | (0.203) | (0.259) |
| Impact after four years  | 0.078 | 0.451 | -0.158\*\* | 0.076 | -0.273 | -0.012 | 0.738 | -0.112 | -0.068 | -0.407 | 0.154 | 0.230 | -0.195\* | 0.135 | -0.145 |
| of intervention | (0.109) | (0.315) | (0.068) | (0.122) | (0.174) | (0.146) | (0.455) | (0.085) | (0.067) | (0.296) | (0.158) | (0.441) | (0.104) | (0.214) | (0.212) |
| Impact after seven years  | -0.002 | 0.389 | -0.085 | 0.200 | -0.453\*\* | -0.0891 | 0.208 | 0.009 | 0.006 | -0.440 | 0.045 | 0.659\* | -0.183\* | 0.372 | -0.518\*\* |
| of intervention | (0.073) | (0.247) | (0.077) | (0.132) | (0.227) | (0.143) | (0.359) | (0.096) | (0.036) | (0.385) | (0.059) | (0.339) | (0.107) | (0.245) | (0.247) |
| Control mean at baseline | 0.056 | 1.305 | 0.0635 | 0.366 | -0.483 | 0.0951 | 1.172 | 0.001 | 0.029 | 0.687 | 0.015 | 1.368 | 0.121 | 0.705 | 0.284 |
| Observations | 7720 | 7720 | 7720 | 7720 | 7720 | 3790 | 3790 | 3790 | 3790 | 3790 | 3930 | 3930 | 3930 | 3930 | 3930 |
| R-sq | 0.016 | 0.190 | 0.046 | 0.021 | 0.033 | 0.033 | 0.183 | 0.067 | 0.032 | 0.046 | 0.024 | 0.209 | 0.046 | 0.041 | 0.047 |
| Panel C: 11 to 14 years |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Impact after two years  | 0.158 | 0.243 | -0.158 | -0.036 | 0.120 | 0.300 | -0.028 | -0.309\* | 0.179 | -0.501 | 0.066 | 0.518 | -0.023 | -0.257 | 0.637 |
| of intervention | (0.161) | (0.338) | (0.118) | (0.349) | (0.404) | (0.323) | (0.504) | (0.165) | (0.262) | (0.531) | (0.043) | (0.450) | (0.171) | (0.599) | (0.587) |
| Impact after four years  | 0.131 | -0.084 | 0.046 | 0.036 | 0.0419 | 0.253 | -0.717 | -0.007 | 0.463\*\* | -0.139 | 0.068\* | 0.689 | 0.103 | -0.390 | 0.154 |
| of intervention | (0.159) | (0.394) | (0.116) | (0.350) | (0.424) | (0.321) | (0.565) | (0.171) | (0.220) | (0.625) | (0.041) | (0.526) | (0.164) | (0.612) | (0.576) |
| Impact after seven years  | 0.0751 | -0.213 | -0.063 | 0.643\* | -0.376 | 0.354 | -0.325 | -0.242 | 0.505\*\* | -0.721 | 0.067 | 0.181 | 0.109 | 0.489 | -0.234 |
| of intervention | (0.163) | (0.336) | (0.109) | (0.339) | (0.377) | (0.317) | (0.481) | (0.148) | (0.235) | (0.494) | (0.043) | (0.460) | (0.155) | (0.597) | (0.549) |
| Control mean at baseline | 0.522 | 8.666 | 0.583 | 3.370 | 2.720 | 1.642 | 6.841 | 0.475 | 1.462 | 1.759 | 0.042 | 9.652 | 0.736 | 4.497 | 3.232 |
| Control baseline characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control sub-districts  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effects  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6158 | 6158 | 6158 | 6158 | 6158 | 2839 | 2839 | 2839 | 2839 | 2839 | 3319 | 3319 | 3319 | 3319 | 3319 |
| R-sq | 0.033 | 0.187 | 0.077 | 0.050 | 0.073 | 0.074 | 0.204 | 0.113 | 0.057 | 0.077 | 0.030 | 0.208 | 0.070 | 0.075 | 0.105 |
| Notes: \*\*\*, \*\*, and \* denote significant at 1%, 5%, and 10% level respectively. Average treatment effect on the treated (ATT) estimates are reported based on a difference-in-difference with triple interaction specification estimated using OLS. The coefficients shown are those on the treatment-survey wave interaction terms. Each coefficient corresponds to a separate regression. The sample includes individuals in the same household as a child of the grant recipient ultra-poor woman. Standard errors are clustered at the individual level. All outcomes are measured at the individual level.  |

## *Does the child labor pronounce more among the older children?*

Table 3 shows the impact of TUP on working hours of the older children age 11 to 14 years in different occupations estimated using Model 3. The triple difference estimates the impact of the program on working hours of secondary school age children (11 to 14 years) against primary school age children (5 to 10 years). In the context of Cambodia, Filmer and Schady (2009) observe that transition from primary to secondary school is the most sensitive times for dropping out in order to work; transfers to children during the transition time to continue school led to a reduction in work. Moreover, primary school age children typically requires less time on study while the secondary age group requires more time on study. We aim to look at whether program intervention has any effect on time allocation of child labor among the older children compared to the younger.

Result shows that average study time of 11 to 14 years treatment kids are likely to reduce significantly by 0.37 standard deviations in the medium term (p<0.10) against the 5 to 10 years control kids while their working hours to agricultural self-employment increase significantly by 0.25, 0.09, and 0.11 standard deviations in the short, medium, and long run, respectively. However, gender disaggregated results show the same trends but for girls only. As can be seen from the results that average working hours of the girls in the program participant households are likely to increase significantly by 0.26 standard deviations on agricultural self-employment in short term (p<0.05), 0.15 standard deviations in the medium term (p<0.05) and 0.14 standard deviations in the longer term (p<0.01). The magnitude of the effects are decreasing over the year as the average working hours of the 11 to 14 years girls in the program participant households are likely to increase significantly by 0.21 standard deviations to non-agricultural skilled employment in the longer run (p<0.10). However, no significant effects observed for boys except 11 to 14 years boys of program participant households are likely to increase average working hours by 0.22 standard deviations on agricultural self-employment in the short run (p<0.05).

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| **Table 3** |  |  |  |
| Impact on working hours for the older children |  |
| 11 to 14 vs 5 to 10 years | Both | Girls | Boys |
| HH chores | Student | Agricultural self-work | Non-agri skilled work | Unskilled work | HH chores | Student | Agricultural self-work | Non-agri skilled work | Unskilled work | HH chores | Student | Agricultural self-work | Non-agri skilled work | Unskilled work |
| Impact after two years  | -0.043 | 0.018 | 0.248\*\*\* | -0.096 | 0.072 | -0.0627 | -0.135 | 0.268\*\*\* | 0.0201 | -0.0646 | 0.002 | 0.175 | 0.215\*\* | -0.223 | 0.156 |
| of intervention | (0.072) | (0.187) | (0.056) | (0.151) | (0.191) | (0.145) | (0.269) | (0.070) | (0.120) | (0.273) | (0.019) | (0.260) | (0.086) | (0.260) | (0.266) |
| Impact after four years  | -0.030 | -0.365\* | 0.092\* | 0.016 | -0.047 | -0.069 | -0.529\* | 0.150\*\* | 0.120 | -0.368 | 0.030 | -0.234 | 0.038 | -0.101 | 0.241 |
| of intervention | (0.072) | (0.203) | (0.054) | (0.145) | (0.189) | (0.138) | (0.290) | (0.068) | (0.105) | (0.275) | (0.034) | (0.280) | (0.082) | (0.255) | (0.258) |
| Impact after seven years  | -0.085 | -0.157 | 0.111\*\* | 0.137 | 0.073 | -0.139 | -0.332 | 0.141\*\* | 0.214\* | 0.073 | 0.008 | -0.024 | 0.072 | 0.036 | 0.127 |
| of intervention | (0.069) | (0.172) | (0.052) | (0.139) | (0.175) | (0.131) | (0.245) | (0.066) | (0.121) | (0.245) | (0.021) | (0.239) | (0.081) | (0.242) | (0.247) |
| Control mean at baseline | 0.192 | 3.445 | 0.115 | 1.179 | 1.358 | 0.506 | 3.076 | 0.028 | 0.457 | 1.419 | 0.028 | 3.707 | 0.199 | 1.810 | 1.242 |
| Control baseline characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control sub-districts  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effects  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 13878 | 13878 | 13878 | 13878 | 13878 | 6629 | 6629 | 6629 | 6629 | 6629 | 7249 | 7249 | 7249 | 7249 | 7249 |
| R-sq | 0.048 | 0.132 | 0.099 | 0.057 | 0.076 | 0.108 | 0.154 | 0.129 | 0.041 | 0.067 | 0.009 | 0.135 | 0.088 | 0.089 | 0.107 |
| Notes: \*\*\*, \*\*, and \* denote significant at 1%, 5%, and 10% level respectively. Average treatment effect on the treated (ATT) estimates are reported based on a difference-in-difference with triple interaction specification estimated using OLS. The coefficients shown are those on the treatment-survey wave interaction terms. Each coefficient corresponds to a separate regression. The sample includes individuals in the same household as a child of the grant recipient ultra-poor woman. Standard errors are clustered at the individual level. All outcomes are measured at the individual level.  |

## *Impact on working hours by baseline employment*

After looking at the average treatment effect on the employment trajectories of the ultra-poor children, we next explore the heterogeneity of the effects of TUP by baseline employment (i.e., in 2007, before program intervention). Table 4 shows the impact of the program on working hours of the kids by baseline employment; both for boys and girls (age 5 to 14 years). The columns are presented for each baseline employment category to showing the incremental effect of the program on working hours between each of the survey year.

Results show that children of program participant households who were involved in household chores at baseline, their average working hours to agricultural self-employment are likely to increase significantly by 0.62 standard deviations in the short run (p<0.01) while their time reduces significantly by 0.35 standard deviations during 2009-2011 (p<0.10) on the same occupation. Daily study time of the children of program participant households who were a student at baseline are likely to reduce significantly by 0.57 standard deviations in the short run (p<0.01) while their time on skilled works increases significantly by 0.21 standard deviations (p<0.01) during the time. Interestingly, we see that average hours of the children of program participant households who were a student at baseline are likely to increase significantly by 0.34 standard deviations on study during 2009-2011 (p<0.01) while their time to unskilled work is likely to decrease significantly by 0.05 standard deviations during the period. Children of program participant households who were involved in agricultural self-employment at baseline are likely to devote 0.67 standard deviations more hours on the same occupation in the short run while their time to study reduces significantly by 1.14 standard deviations during 2011-2014. No significant transition observes among the children who were involved in non-agricultural skilled employment at baseline. However, children of program participant households who worked unskilled works at baseline are likely to increase average working hours by 0.48 standard deviations to households chores (p<0.01), 0.44 standard deviations to study (p<0.05), and 0.43 standard deviations to agricultural self-employment (p<0.01) during 2007-2009. Their time to non-agricultural skilled works decrease significantly by 1.12 standard deviations during the period (p<0.10). However, no incremental effects observed in the other period. Del Carpio et al. (2016) pointed out that women in grant recipient households are likely to devote themselves more towards income-generating activities, this might increase the return to a female child’s labor in these activities or even in domestic tasks to substitute for mother’s work.

These results imply that after receiving program support, the children of the program participant households are likely to spend more time on household chores and agricultural self-employment to supplement the work of their mothers. Notably, findings show that the children of program participant households are likely to shift to better occupation like household chores, study, and agricultural self-employment from the unskilled work in the short run against the children of non-participant households.

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| **Table 4** |  |  |  |  |  |
| Impact on working hours of the children by baseline employment; both for boys and girls (age 5 to 14 years) |  |  |
| For both boys and girls | HH chores | Student | Agricultural self-work | Non-agri skilled work | Unskilled works |
|  (Average hour/day) | 2007-2009 | 2009-2011 | 2011-2014 | 2007-2009 | 2009-2011 | 2011-2014 | 2007-2009 | 2009-2011 | 2011-2014 | 2007-2009 | 2009-2011 | 2011-2014 | 2007-2009 | 2009-2011 | 2011-2014 |
| HH chores | -0.421 | 0.048 | -0.275 | -0.008 | 0.016 | -0.009 | -0.127 | -0.071 | -0.092 | 0.174 | -0.111 | -0.065 | 0.477\*\*\* | 0.224 | 0.250 |
|   | (0.394) | (0.663) | (0.688) | (0.025) | (0.022) | (0.021) | (0.190) | (0.129) | (0.132) | (0.124) | (0.124) | (0.064) | (0.153) | (0.173) | (0.427) |
| Student | -0.960 | -0.459 | 0.632 | -0.570\*\*\* | 0.337\*\*\* | 0.041 | -0.217 | 0.418 | -1.135\*\*\* | -0.050 | 0.056 | -0.324 | 0.444\*\* | -0.251 | -0.820 |
|   | (0.647) | (0.753) | (0.840) | (0.099) | (0.105) | (0.096) | (0.438) | (0.384) | (0.368) | (0.335) | (0.465) | (0.631) | (0.186) | (0.534) | (0.547) |
| Agricultural self-work | 0.625\*\*\* | -0.356\* | -0.091 | 0.210\*\*\* | 0.030 | 0.080\*\*\* | 0.673\*\* | -0.021 | 0.092 | 0.239 | -0.239 | 0.018 | 0.432\*\*\* | 0.054 | -0.064 |
|   | (0.225) | (0.196) | (0.196) | (0.024) | (0.023) | (0.026) | (0.297) | (0.151) | (0.138) | (0.240) | (0.168) | (0.173) | (0.153) | (0.209) | (0.124) |
| Non-agri skilled work | 0.350 | -0.244 | -0.548 | -0.057 | 0.026 | 0.045 | 0.238 | -0.223 | -0.0934 | -0.383 | 0.121 | 1.555 | -1.206\* | -0.290 | 0.846 |
|   | (0.573) | (0.271) | (0.579) | (0.044) | (0.036) | (0.046) | (0.267) | (0.213) | (0.363) | (1.070) | (1.104) | (1.658) | (0.641) | (0.701) | (0.799) |
| Unskilled works | -0.142 | -0.570 | 0.636 | -0.019 | -0.054\* | -0.012 | 0.301 | 0.264 | 0.115 | 0.292 | 0.172 | 0.137 | -0.416 | -0.0610 | 0.945 |
|   | (0.459) | (0.620) | (0.456) | (0.042) | (0.032) | (0.03) | (0.375) | (0.256) | (0.242) | (0.449) | (0.472) | (0.359) | (0.835) | (1.018) | (1.331) |
| Control baseline characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control sub-districts  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effects  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 205 | 171 | 128 | 4422 | 4794 | 4951 | 291 | 783 | 660 | 217 | 192 | 128 | 370 | 247 | 174 |
| Notes: \*\*\*, \*\*, and \* denote significant at 1%, 5%, and 10% level respectively. The columns are presented for each baseline employment category to showing incremental effect of the program on working hours. Average treatment effect on the treated (ATT) estimates are reported based on a difference-indifference specification estimated using OLS. The coefficients shown are those on the treatment-survey wave interaction terms. Each coefficient corresponds to a separate regression. The sample includes individuals in the same household as a child of the grant recipient ultra-poor woman. Standard errors are clustered at the individual level. All outcomes are measured at the individual level.  |

## *Impact on working hours of the children age 5 to 8 years at baseline*

Further, to look at the heterogeneous of the impact of the program, we also explore the impact of the program on working hours of the kids whose age was 5 to 8 years at baseline i.e., in 2007. We intend to look at the employment trajectories of this group over the years as they were among the younger group at baseline and their maximum age will be 14 years until the last round of survey (i.e., in 2014). So, it is interesting to look at how and in which occupation the kids are spending their time after the intervention. As can be seen from Table 5, children of program participant households age 5 to 8 years who were at the household at baseline, are likely to spend on average 0.60 standard deviations less time on study after two years (p<0.01) and 0.34 standard deviations after four years of intervention (p<0.05) compared to the children of non-participant households. While the kids of this age group of participant households are likely to significantly increase their time on agricultural self-employment by 0.14 standard deviations in the short run (p<0.01), 0.16 standard deviations in the medium run, and 0.32 standard deviations in the longer run (p<0.01). No significant differences observe among the children of participant and non-participant households on their time devoted to non-agricultural skilled and unskilled employment.

Gender disaggregated result shows that female children in the program participant households are likely to spend less time on study in the short, medium and long run while they spend more time on agricultural self-employment over the year (p<0.01) compared to those in the control households. Daily average working hours of the former are likely to increase significantly by 0.05, and 0.27 standard deviations after four (p<0.10) and seven years (p<0.01) of intervention respectively on non-agricultural skilled employment. However, the study time of the male children in the program participant households is likely to reduce by 0.52 standard deviations on study in the short run while spending 0.14 standard deviations more time on agricultural self-employment in the short and medium term and 0.19 standard deviations in the longer run. The average working hours of the boys of participant households are likely to reduce significantly by 0.25 standard deviations on unskilled work in the longer run (p<0.05).

|  |  |  |  |
| --- | --- | --- | --- |
| **Table 5** |  |  |  |
| Impact on working hours of the children aged 5 to 8 years at baseline (2007) |  |
|  | Both | Girls | Boys |
|   | HH chores | Student | Agricultural self-work | Non-agri skilled work | Unskilled work | HH chores | Student | Agricultural self-work | Non-agri skilled work | Unskilled work | HH chores | Student | Agricultural self-work | Non-agri skilled work | Unskilled work |
| Impact after two years  | -0.005 | -0.603\*\*\* | 0.138\*\*\* | -0.003 | 0.036 | -0.008 | -0.700\*\*\* | 0.134\*\*\* | 0.003 | 0.058 | -0.004 | -0.524\*\*\* | 0.144\*\*\* | 0.0004 | 0.022 |
| of intervention | (0.017) | (0.112) | (0.021) | (0.0258) | (0.045) | (0.036) | (0.164) | (0.033) | (0.007) | (0.06) | (0.008) | (0.156) | (0.027) | (0.050) | (0.059) |
| Impact after four years  | -0.035 | -0.342\*\* | 0.164\*\*\* | 0.009 | -0.032 | -0.066 | -0.448\*\* | 0.193\*\*\* | 0.0540\* | 0.008 | -0.004 | -0.247 | 0.141\*\*\* | -0.033 | -0.065 |
| of intervention | (0.037) | (0.145) | (0.029) | (0.066) | (0.062) | (0.076) | (0.216) | (0.045) | (0.031) | (0.105) | (0.008) | (0.199) | (0.039) | (0.121) | (0.069) |
| Impact after seven years  | -0.017 | -0.047 | 0.187\*\*\* | 0.136 | -0.105 | -0.021 | -0.335\* | 0.188\*\*\* | 0.273\*\*\* | 0.071 | -0.006 | 0.216 | 0.186\*\*\* | 0.0201 | -0.250\*\* |
| of intervention | (0.049) | (0.141) | (0.043) | (0.102) | (0.087) | (0.105) | (0.191) | (0.066) | (0.097) | (0.113) | (0.007) | (0.200) | (0.058) | (0.168) | (0.127) |
| Control mean at baseline | 0.286 | 3.096 | 0.017 | 0.741 | 0.743 | 0.573 | 2.766 | 0.104 | 0.339 | 0.707 | 0.009 | 3.606 | 0.128 | 1.151 | 0.832 |
| Control baseline characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control sub-districts  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual fixed effects  | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4385 | 4385 | 4385 | 4385 | 4385 | 2070 | 2070 | 2070 | 2070 | 2070 | 2315 | 2315 | 2315 | 2315 | 2315 |
| R-sq | 0.041 | 0.208 | 0.112 | 0.054 | 0.042 | 0.093 | 0.210 | 0.126 | 0.061 | 0.036 | 0.010 | 0.226 | 0.114 | 0.084 | 0.080 |
| Notes: \*\*\*, \*\*, and \* denote significant at 1%, 5%, and 10% level respectively. Average treatment effect on the treated (ATT) estimates are reported based on a difference-indifference specification estimated using OLS. The coefficients shown are those on the treatment-survey wave interaction terms. Each coefficient corresponds to a separate regression. The sample includes individuals in the same household as a child of the grant recipient ultra-poor woman. Standard errors are clustered at the individual level. All outcomes are measured at the individual level. |

# Conclusions

Child labor is higher in the Asia and the Pacific region, and most of them are involved in the informal sectors such as in small factories and workshops, on the street, in home-based businesses and domestic employment. Studies show that the conditional cash transfer program where the transfer is conditional upon children attending school positively impacts on school enrolment but find mixed effects on reduction of work. Literature on impact of the cash transfer program that directly targets the children on time allocation of child labor is available while the impact of asset transfer program that targets the main female of the households on time allocation of child labor in the long run is largely lacking. This study aims to explore how does the grant-based *asset transfer program* impact on time allocation of child labor of the ultra-poor children in the long run using longitudinal data from Randomized Controlled Trials of the TUP program. We estimate the impact of the program on time allocation of child labor using a triple differenced model.

Findings show that asset transfer significantly increases the likelihood of adopting entrepreneurship over the year among the children of the program recipients. Daily working hours of the 5 to 14 years children of TUP households are likely to increase significantly in agricultural self-employment in the short, medium, and long run. While their study time reduces significantly in the short and long run, no significant impacts observe on households chores, non-agricultural skilled, and unskilled works. Gender disaggregated results show that study time of the female child of the program participant households are likely to reduce significantly in the short, medium and longer term while their time to agricultural self-employment increases significantly over the year. Interestingly, girls in the program households are likely to devote more time to non-agricultural skilled work in the longer run. For working hours of boys, we find the same trends for study in the short run only, and for agricultural self-employment in the short, medium, and longer run; no significant impact observes for the other employment categories.

Evidence shows that children’s time allocation to productive works varies across gender of the household head. Results show that children of male-headed program participant households are likely to spend significantly less time on agricultural self-employment in the short and long run while dedicating significantly more time on non-agricultural skilled employment in the long run. Secondary school age female children of male-headed program participant households are likely to devote significantly more time on non-agricultural skilled work in the medium and long run. Substantial effects observe for primary school age boys of male-headed households where they are likely to dedicate less time on unskilled work like day laboring in the long run but more time on non-agricultural skilled work in the short run.

While looking at the impact of the program on whether child labor is higher among the older children (age 11 to 14 years) against the younger (age 5 to 10 years), result shows that study time of the older children of treatment households reduce significantly in the medium term while their working hours to agricultural self-employment increase significantly in the short, medium, and longer run. Gender disaggregated result shows the same trend for girls of treatment households. Additionally, girls of treatment households are likely to spend significantly more time on non-agricultural skilled work in the longer term. However, no significant effects observe for boys except 11 to 14 years boys of program participant households are likely to spend significantly more time on agricultural self-employment in the short run.

Further, the heterogeneous effects of TUP by baseline employment shows that children of program participant households who were involved in household chores at baseline, they are likely to spend more time on agricultural self-employment in the short run while spending less during 2009-2011 on the same occupation. Children of program participant households who were a student at baseline are likely to spend less time on study during 2007-2009 but spend more time on study during 2009 -2011. They are likely to spend more time on agricultural self-employment during 2007-2009 and 2011-2014. However, children of program participant households who were involved in agricultural self-employment at baseline are likely to devote more time on the same occupation in the short run while their time to study reduces significantly by during 2011-2014. Children of program participant households who worked unskilled works at baseline are likely to spend significantly more time to better occupation like household chores, study, and agricultural self-employment during 2007-2009.

Children of program participant households age 5 to 8 years children who were at the household at baseline, they are likely to spend less time on study after two years and four years of intervention. While the kids of this age group of participant households are likely to devote significantly more time on agricultural self-employment in the short, medium and long run. The gender disaggregated result shows almost the trend. However, it is notable that female children in the program participant households are likely to spend significantly more time on non-agricultural skilled employment after four and seven years of intervention while boys of program participant households are likely to devote significantly less time on unskilled work in the longer run.

On the one hand, our findings correspond to the studies where authors claim that the eligible grant recipient households are more likely to inject their children into the labor market. On the other hand, our study provides valuable insights that the *asset transfer program* impacts on child labor by improving their time allocation to agri- and non-agricultural self and skilled employment in the medium and long run. However, we suggest that child labor elimination policies should focus on financial support that would supplement their labor cost for survival, ensure access to quality education, and generate better economic opportunities.

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# Annexure

## Table A.1 Summary statistics of control variables at baseline

|  |  |  |  |
| --- | --- | --- | --- |
| Indicators | Coefficient | Std. Err. | P value |
| Respondents age (years) | 0.001 | 0.002 | 0.635 |
| Male-headed household (1/0) | -0.052 | 0.045 | 0.249 |
| Household size | 0.002 | 0.018 | 0.889 |
| Per capita income (BDT) | -0.005 | 0.008 | 0.521 |
| HHs could manage at least two meals in a day (1/0) | 0.009 | 0.154 | 0.955 |
| HHs had available or surplus food in last one year (1/0) | 0.047 | 0.206 | 0.818 |
| **Education of the respondent** |  |  |  |
| No education (1/0) | 0.012 | 0.083 | 0.888 |
| Primary education (1/0) | 0.013 | 0.112 | 0.910 |
| **Employment of respondent** |  |  |  |
| Self-employment (1/0) | -0.041 | 0.126 | 0.744 |
| Wage-employment (1/0) | -0.117 | 0.154 | 0.447 |
| Work as maid (1/0) | -0.083 | 0.078 | 0.288 |
| Involved in begging (1/0) | -0.026 | 0.136 | 0.846 |
| **Assets** |  |  |  |
| HHs own any land (1/0) | 0.020 | 0.041 | 0.634 |
| HHs own any livestock (1/0) | -0.031 | 0.063 | 0.628 |
| HHs have saving (1/0) | 0.090 | 0.127 | 0.479 |
| HHs own radio/television (1/0) | -0.040 | 0.129 | 0.755 |
| HHs own cell phone (1/0) | -0.017 | 0.329 | 0.960 |
| HHs have wall made of concrete (1/0) | 0.115 | 0.272 | 0.672 |
| Observation | 5042 |  |  |
| Pseudo R2 | 0.049 |  |  |

##

**Table A.1**

Daily working hours of the children age 5 to 14 year at baseline

|  |  |  |  |
| --- | --- | --- | --- |
| Employment category | Treatment | Control | Difference |
| HH chores | 0.152 | 0.132 | 0.020 |
| Student | 2.376 | 2.480 | -0.104\* |
| Agricultural self-work | 0.081 | 0.094 | -0.013 |
| Non agri skilled work | 0.242 | 0.237 | 0.006 |
| Unskilled work | 0.447 | 0.528 | -0.080 |
| Observation | 2,048 | 1,099 |  |

1. https://en.wikipedia.org/wiki/Child\_labor\_in\_Bangladesh [↑](#footnote-ref-1)
2. [https://www.unicef.org/bangladesh/children\_4863.html](https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=14&cad=rja&uact=8&ved=2ahUKEwicr4vw6fPeAhVDWH0KHaB6AiUQFjANegQIBxAQ&url=https%3A%2F%2Fwww.unicef.org%2Fbangladesh%2Fchildren_4863.html&usg=AOvVaw2BKq4uoOHI90oJn7UC46Ug) [↑](#footnote-ref-2)
3. An American Social Worker & Child Labor Reformer Director, Children's Bureau, U.S. Department of

Labor 1917,1934. https://www.ilo.org/century/history/iloandyou/WCMS\_180170/lang--en/index.htm [↑](#footnote-ref-3)
4. BRAC is the pioneer of the TUP program that targets those who are living below the poverty line, includes direct transfers of income generating livestock assets/soft loan and livelihood training. Since its inception in 2002, it reaches around 1.77 million extreme poor households covering 50 of 64 districts of Bangladesh. [↑](#footnote-ref-4)
5. The TUP program offers low interest rate (20%) while regular BRAC microfinance program or other MFIs for example, ASA, another large MFIs in Bangladesh charge 25 per cent interest rate ([www.asa.org.bd/loan-product/](http://www.asa.org.bd/loan-product/)). Additionally, the program participants get the opportunity to pay the installment after two months of taking the loan. [↑](#footnote-ref-5)
6. For this holistic intervention to move the extreme poor out of poverty, the graduation approach has now been well recognized around the globe and adapted by 114 programs in 45 countries by government and non-government organizations in the world’s most poverty concentrated areas. [↑](#footnote-ref-6)
7. http://www.brac.net/images/index/tup/brac\_TUP-briefNote-Jun17.pdf [↑](#footnote-ref-7)
8. In this phase, 300,000 ultra-poor households were covered from 40 poorest districts. [↑](#footnote-ref-8)
9. The selection criteria of OTUP support package includes (1) Household owns ≤30 decimals of land, (2) Unable to bear children’s education expenses beyond the primary level, (3) Household is mainly dependent on irregular income, (4) History of failure to make successful use of NGO support in the past, (5) Failure to avail either fish or meat or eggs in the last three consecutive days. [↑](#footnote-ref-9)
10. Although the overall objective of the intervention is to improve the welfare of all family members, program support is given to the main female member of the selected household. [↑](#footnote-ref-10)
11. OTUP support package provides consumption support and soft loan along with livelihood and life skill training, provides savings, health, and legal services to uplift them out form extreme poverty. [↑](#footnote-ref-11)
12. This supervision performs a crucial role to confirm that the participants’ are being operative and enjoy ownership. This close and longer period supervision is rare in other social protection programs operated in Bangladesh. [↑](#footnote-ref-12)
13. Designation of the staff is Program Organizer (PO) [↑](#footnote-ref-13)
14. Issues include early childhood marriage and dowry, human trafficking, domestic violence, children’s education, marriage registration, disaster preparedness, waterborne diseases, de-worming, food nutrition, and anaemia, non-communicable diseases, family planning, and immunisation. [↑](#footnote-ref-14)
15. Lakdawala (2018) finds that households in the middle of the wealth distribution become involved in the business after getting access to credit that concurrently increases their use of child labor, but no effect observes on school attendance or dropout rates. [↑](#footnote-ref-15)
16. Occupations that have less social values like a day laborer, maid, begging, etc. [↑](#footnote-ref-16)
17. The baseline survey was conducted from May to December 2007. The first and second follow up survey were conducted during July-December 2009, and November 2010-May 2011, respectively. And the third and final round survey was conducted between December 2013 and April 2014. [↑](#footnote-ref-17)
18. The first phase of the TUP program was implemented in 2002, where non-experimental evaluation design was adopted in the evaluation design in the three northern districts (Rangpur, Kurigram, Nilphamari) of Bangladesh. [↑](#footnote-ref-18)
19. Baseline survey branches were from 13 districts (Chapainobabgonj, Kishorgonj, Madaripur, Naogan, Netrokona, Sherajgonj, Thakurgaon, Ponchogorh, Nilphamari, Lalmonirhat, Kurigram, Gaibandha, and Rangpur). [↑](#footnote-ref-19)
20. TUP program operates at the branch level that covers areas within a 5 km radius. [↑](#footnote-ref-20)
21. Finally, selected households of treated branches receive program support while finally selected households of control branches will not offer any program support. [↑](#footnote-ref-21)
22. Banerjee *et al.* (2015) in such kind of asset transfer program find 17% and 21 % attrition in India and Pakistan, respectively. [↑](#footnote-ref-22)
23. To reduce the attrition rate, research assistants were instructed to collect household information from another adult female (for example respondent’s daughter or daughter in law) of the household if the main respondent is absent or died during the survey. If respondent changes, we eliminate these households from our analysis. [↑](#footnote-ref-23)
24. Evaluation sample include 3,147, 3,527, 3,549, and 3655 children in 2007, 2009, 2011, and 2014. [↑](#footnote-ref-24)
25. Edmonds and Theoharides (2018) anticipate a 50 per cent decline of child labor as the transfer of the program was conditional upon reducing/eliminating child labor. In our study, the program’s focus is on economic improvement. We assume that it would be too ambitious to anticipate that households’ financial improvement would reduce 50% of child labor. [↑](#footnote-ref-25)