Skip all front matter: Jump to Page 1

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DISSERTATION

Three Essays on Child Labor and Education in Developing Countries

Seo Yeon Hong

RAND PARDEE RAND GRADUATE SCHOOL

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This document was submitted as a dissertation in June 2013 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of Krishna Kumar (Chair), Peter Glick, and Paco Martorell.

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Table of Contents

Abstract

This dissertation seeks to understand the mechanism of a household's decision on child labor and educational investment by proposing a theoretical framework, examining the empirical evidence, and providing policy evaluation and recommendations.

In the theoretical framework, I address the factors related to the educational investment and child labor such as living below the subsistence level of consumption (poverty), the opportunity cost of education (the child's wage), and the return to education. The first chapter focuses on the household's educational investment decision over the life cycle and addresses the effect of birth order on the educational attainment and child labor supply under binding budget and credit constraints. The empirical evidence from Tanzania suggests there are 'delays' in schooling for the latter-born children and 'school dropout' for the earlier-born children. In the second chapter, I empirically estimate the labor supply for children in the family farm in Tanzania. The supply curve is downward sloping, suggesting that poverty is the main cause of child labor. The third chapter focuses on the evaluation of specific policies designed to encourage the educational investment for girls - the reduction of tuition and the provision of a stipend in Bangladesh. This program is intended to promote the female education by lowering the cost of schooling. I evaluate the long-term effect of the program by estimating the effect on completed years of schooling, age of marriage, and labor force participation of married women.

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Chapter 1. The Birth Order Effect on Education and Child Labor: Delaying school enrollment vs. Dropping out of school

I. Introduction

The parental educational investment on children depends on income of household and expected returns of the educational investment. With the perfect credit market, equal attitude and level of attention devoted to each child (herein referred to as 'altruistic factor'), and equal genetic endowment of each child, we expect no significant sibling difference in educational outcome. However, a large body of economic literature has shown the evidence to the contrary, suggesting that the sibling difference exists.

Sibling differences in educational outcome can occur through multiple channels, and the economic reason is the most widely discussed in the literature. When there is a biding budget constraint and credit market does not function perfectly, parents cannot smooth the household's consumption (e.g. education spending) over the life cycle. In this case, the first-born and the last-born children are most favored due to the least competition over limited economic resources. Consequently, the children born in the middle receive the least educational investment (Birdshall, 1991). Another set of studies suggests that the birth order effect stems from the difference in earning potentials between siblings. Household makes educational investment on children taking into account their future earnings; thus, child with the most prominent future earning potential (returns to education) may receive the most educational investment. For example, the gender difference in education in Asia can be explained by the relatively low returns to education attained by females due to their low participation in labor market (Parish and Willis, 1993). If there is genetic difference between siblings, such as IQ or health of child, parents invest more on the smarter child, expecting higher future earnings. Ejrnaes and Portner (2004) relate the genetic endowment of child with fertility decision, and show that—assuming parents stop having children once they have a child with high genetic endowment—the latter-born child receives more educational investment from the parents. Some studies also focus on the parental time and income, and relating it to the educational attainment and consider the birth order effect arising as child grows (Behrman and Taubman, 1986; Gugl and Welling, 2010).

The theory of sibling difference in education, however, does not consider the income generated by other siblings, which is a main source of income for many poor households in the world. On the other hand, economic literature on child labor has focused on relatively higher opportunity cost of the earlier-born children to explain the sibling difference in child labor. Empirical evidence supports the claim that the earlier-born child is more likely to work when there is a severe binding budget constraint. Dammert (2010) found that, in Nicaragua, the older boys spend more time working, whereas older girls spend more time doing domestic work than the younger siblings. Similarly, Emerson and Souza (2008) found the youngest child is less likely to work, compared to older siblings in Brazil. Most of empirical studies, however, have looked at the birth order effect on child labor from the single-period point of view (Dahan and Gaviria, 2003; Dammert, 2010; Edmonds, 2006; Emerson and Souza, 2008). However, when the relative opportunity cost of education varies depending on the age of the children in family, these findings can mislead the understanding of birth order effect.

This study combines the economic literature of education and child labor and develops the theoretical framework of the birth order effect based on "multi-periods" utility maximization problem[1]. In the model, I consider the competition over limited resources between siblings, the

[1] Gugle and Welling (2010) present the multi-period utility maximization problem to explain the birth order effect arising as a child grows. It is more relevant when budget or credit constraints are not binding, and it

earlier realization of older sibling's returns to education (e.g. higher discount rate for the younger sibling), the older sibling's higher opportunity cost as the child grows, and the older sibling's income effect on the younger sibling's education. Empirically, I first analyze the birth order effect on school enrollment and working, depending on the age of the child, for children ages 7 to 17 years. I subsequently investigate the birth order effect on completed years of education for the same children using their adulthood information, based on the Kagera Health and Development Survey panel data (KHDS in 1991-1994, and 2004).

The paper is structured as follows; in section II, the theoretical framework of the birth order effect on education and child labor is presented, with feasible assumptions for poor households in developing countries; section III is devoted to the data and empirical strategy; in section VI, I discuss the results; and the conclusion and discussion is presented in section V.

II. Theoretical Framework

The theoretical framework developed in this study can be generalizable in the context of developing countries. The key assumption made here is that altruistic parents make a decision on educational investment by maximizing the utility from consumption, in addition to the discounted returns to education of their children. This study further assumes that: (i) the first-born child has lower discounting rate of the returns to education than the latter-born child, since the first-born child's return will be realized earlier; (ii) there is no genetic difference between siblings; (iii) household cannot smooth the consumption over time due to the imperfect credit market; and (vi) fertility decision is not endogenous, given the low utility rate of the contraceptive method in the region. For the ease of presentation, the model includes only two children, whereby the first-born

also puts emphasis on parental time and income. This study focuses on the birth order effect changing over time due to the binding budget and credit constraints.

child represents the earlier-born children, and the second-born child represents the later-born children.

Household maximizes following utility (V) subject to the budget constraint is given by:

$$V_t = \log(c_t - \bar{c}) + \beta_t(e_{1t}v_{s,t} + (1-e_{1t})v_{u,t}) + \beta_t^2(e_{2t}v_{s,t} + (1-e_{2t})v_{u,t}) \text{ , } t = 0,1,2,3$$

$$\text{s.t. } c_t + \sum_{i=1}^{2} p_{it} \le w_{At} + \sum_{i=1}^{2}(1-e_{it})w_{it}$$

The above expression implies that parents derive the utility from the net consumption $c_t - \bar{c}$, where c_t is household consumption at t and $\bar{c}$ is subsistence level of consumption, in addition to the discounted value of returns to education for both children ($e_{1t}v_{s,t} + (1-e_{1t})v_{u,t}$). Here, e_{1t} indexes the educational investment for the first-born child at t ($e_{1t} = [0,1]$; with 0 and 1 indicating no schooling or schooling, respectively) and e_{2t} indexes the latter-born child's educational investment at t ($e_{2t} = [0,1]$). Similarly, v_s indexes the educated child's return in the future, and v_u is the uneducated child's return in the future. β_t is a discounting factor for the returns to education ($0 < \beta_t < 1$) at t. Finally, since the first-born child's returns to education will be realized sooner than that of the latter-born child, the discounting factor for the latter-born child is given as β_t^2.

Household maximizes the utility subject to the current budget constraint, depending on the child's earnings (w_{it}), adults' earnings (w_{At}), and the price of education (p_{it}), whereby p_{it} and w_{it} vary depending on the child's age.

Here, it is assumed that household can optimize the educational investment by maximizing the utility at each period, defined as follows: (i) when only the first-born child is school-age, referred to as initial period (t = 0); (ii) when both the first-born child and the latter-born child are young school-age—first period[2] (t = 1); (iii) when the first-born child is older school-age, while the latter-born child is young school-age, referred to as second period (t = 2); and (iv) when only the latter-born child is still of school-age, third period (t = 3).

1. Multi-Period Utility Maximization

a) Initial Period, t = 0

When only the first child is of school age, the household maximizes the following function.

$$V_0 = \log(w_{A0} + (1-e_{10})w_{10} - p_{10} - \bar{c}) + \beta_0(e_{10}v_s + (1-e_{10})v_u)$$

Thus, the first child is sent to school if $V_0(e_{10}=1) > V_0(e_{10}=0)$.

That implies that $e_{10}^* = 1$ if $\log(\frac{w_{A0} + w_{10} - \bar{c}}{w_{A0} - p_{10} - \bar{c}}) < \beta_0(v_s - v_u)$ --- Condition 1

It is evident from the above that Condition 1 is more likely to be satisfied if: (i) the expected returns to education ($\beta_0(v_s - v_u)$) increase; and/or (ii) the schooling cost (p_{10}) and child wage (w_{10}) decreases.

[2] I denote this as the first period since this is the first period that parents have to make a decision on *which* child is sent to school.

b) First Period, t = 1

When both children are still young (e.g. aged 7 to 12), the household maximizes the utility (V_1). Since both children are young and of similar age, identical schooling cost and wage for each child is assumed ($p_{12} = p_{22}$; $w_{12} = w_{22}$).

$$V_1 = \log(w_{A1} + (1-e_{11})w_{11} + (1-e_{21})w_{21} - p_{11} - p_{21} - \overline{c}) + \beta_1(e_{11}v_s + (1-e_{11})v_u) + \beta_1^2(e_{21}v_s + (1-e_{21})v_u)$$

Comparing four different states,

$V_1(e_{11} = 1; e_{21} = 1); V_1(e_{11} = 1; e_{21} = 0); V_1(e_{11} = 0; e_{21} = 1); V_1(e_{11} = 0; e_{21} = 0)$, parents make following decision.

First, if the adults' earnings are sufficient to cover the schooling cost of both children and the subsistence level of consumption ($w_{A1} - p_{11} - p_{21} - \overline{c} < 0$), both children would be sent to school ($e_{11}^* = 1; e_{21}^* = 1$).

However, if parents had to choose one child to send to school (($V_1(e_{11} = 1; e_{21} = 0)$ or $V_2(e_{11} = 0; e_{21} = 1)$), implying that the earnings of adults and the earning of one child are enough to cover the other child's schooling cost, then the first-born is more likely to be sent to school ($e_{11}^* = 1; e_{21}^* = 0$) than the latter-born. This is because the first-born child is older, and thus parents expect the returns of the educational investment be realized earlier for the first-born child than the latter-born child, $\beta_1(v_s - v_u) > \beta_1^2(v_s - v_u)$ (Condition 2).

Finally, when the household is extremely poor, no sibling difference in terms of schooling is expected, since both children are not sent to school ($e_{11}^{*} = 0; e_{21}^{*} = 0$).

c) Second Period, t=2

When the first-born is of older school-age (e.g. aged 13 to 17 or secondary school-age) and the latter-born child is of young school-age (e.g. 7 to 12 of primary school-age), the utility at this period is similar to the one at the first period (t = 1). However, the first-born child is old enough to earn higher wage than the second-born child, and the cost of secondary education is higher than the cost of primary education. Therefore, the key difference between this period and the previous period is the first-born child's schooling cost and wage are higher than the ones of the latter-born child ($p_{12} > p_{22}$; $w_{12} > w_{22}$), which shifts the decision to school only one child towards the younger sibling.

Akin to the first period (t = 1), if the schooling cost of both children and the subsistence level of consumption exceed the earnings of adults ($w_{A2} - p_{12} - p_{22} - \overline{c} < 0$), which is more likely than the first period due to the higher schooling cost, one or both of the children will not be sent to school. However, the tension between two children over the limited resources is more nuanced than the first period, since their opportunity cost of schooling (w_{12}; w_{22}) and education cost (p_{12}; p_{22}) differ as well as the discounting factor of returns to education (β_2; β_2^2).

Thus, considering the case whereby only one child is sent to school, if the following condition is satisfied, the first-born child is sent to work, while the latter-born child is sent to school.

$$\beta_2(v_s - v_u) < \log(\frac{w_{A2} + w_{12} - p_{22} - \bar{c}}{w_{A2} + w_{22} - p_{12} - \bar{c}}) + \beta_2^2(v_s - v_u) \text{ --- Condition 3}$$

Compared to the Condition 2 at the first period, the likelihood of first-born child going to school is lower at this period due to the additional term in Condition 3, $\log(\frac{w_{A2} + w_{12} - p_{22} - \bar{c}}{w_{A2} + w_{22} - p_{12} - \bar{c}}) > 0$, which refers to the higher opportunity cost of schooling of the first-born child and lower schooling cost of the latter-born child.

In sum, if adult's earnings are not sufficient to cover both children's schooling cost, when both children are young, the latter-born child is less likely to be sent to school compared to the first-born child (delay in schooling). However, as the first child's schooling cost becomes greater in the second period, the relative likelihood of first-born child going to school declines. .

d) Third Period, t = 3

When only the latter-born child is of school-age, household maximizes the following utility:

$$U = \log(w_{A3} + w_{13} + (1 - e_{23})w_{23} - p_{23} - \bar{c}) + \beta_3(e_{23}v_s + (1 - e_{23})v_u)$$

In this period, the latter-born child is sent to school if the expected returns to education are greater than the relative utility gain of sending children to work rather than to school,

$$\log(\frac{w_{A3} + w_{13} + w_{23} - \bar{c}}{w_{A3} + w_{13} - p_{23} - \bar{c}}) < \beta_3(v_s - v_u).$$

In summary, the first-born child's education in the initial period (t = 0) is determined by adult earnings only. Subsequently, in the first period (t = 1), the first-born child is more likely to go to school compared to the latter-born child, since parents expect to realize educational investment of the first–born child earlier than the latter-born child.[3] In the second period (t = 2), however, the likelihood of schooling of the first-born child declines compared to the first period, since the first-born child's schooling cost becomes higher than the latter-born child's. In addition, their earning potential increases, making it more cost effective to send the first-born child to work. In the third period (t = 3), the educational investment on the latter-born child is the highest due to the additional income from the first-child's working and less competition between siblings.

Due to the above dynamics, 'delays' in schooling for the latter-born child can be expected when older siblings are still young and similar in age. However, the likelihood of the latter-born child going to school becomes greater as the older sibling's opportunity cost of schooling becomes higher. In particular, the sibling differences in school enrollment and educational attainment are expected to vary over time for households at the margin—in families where adult earnings are sufficient to cover only one child's schooling cost. For extremely poor households, the conditions of the educational investment for any child are hard to be satisfied; hence it is unlikely that any children will be sent to school, implying little sibling difference. In contrast, for households with high income, the conditions of the educational investment for both children are likely to be satisfied.

In order to show the variation in the birth order effect over time empirically, subsequent sections demonstrate the birth order effect on school enrollment and working change depending on child's age. The data and empirical strategy employed in this study are presented next more in detail.

[3] This holds only when the first child is sent to school in the initial period. If that is not the case, i.e. the household is too poor, then the later born child is going to be sent to school in the first period instead, if at all.

III. Data and Empirical Strategy

1. Data

Kagera Health and Development Survey (KHDS) is a longitudinal survey conducted by the World Bank. Kagera is located in North West of Tanzania, covering four different agro-climatic zones, with 92 % of KHDS households engaged in agriculture[4] in 1991-1994. This region in Tanzania suffered from the AIDS epidemic in the late 80s and the early 90s. Moreover, according to Sarris and Tinios (1990), 54% of the households in rural Tanzania lived under the poverty line and consumed 2000 calories per day.

The survey was fielded annually from 1991 to 1994 as well as in 2004. 912 households were surveyed during the first four years (1991-1994) and, in 2004, the household members[5] (91 percent follow-up rate at household level) were re-interviewed. This study uses the first four sets (1991-94) of the KHDS data to study the birth order effect on school enrollment and working of children age 7 to 17 years. Moreover, the 2004 KHDS is utilized to investigate the birth order effect on the complete educational attainment for the children included in 1990-1994[6] data sample (adulthood sample). 65% of the children included in the 1991-1994 data set were matched to their adulthood information of the 2004 survey. I used logistic regression of successful match to check non-random attrition (Appendix, Table 1). Covariates of baseline characteristics in 1991-1994 are used to estimate the probability of successful match, and using this probability, I calculated the inverse probability weight (IPW) in order to correct the potential attrition bias. The result shows that there is no systematic match in terms of birth order and value of asset; however, children who worked at their family farm, were younger aged, from more land-holding

[4] Defined as at least one person in the household working at the family farm. The number is based on the author's calculation.
[5] At least one person from the household in 1991-1994 was traced and re-interviewed in 2004.
[6] The youngest cohort is 17 years old in 2004 KHDS sample

household, with farm-worker parents, and whose father died are positively correlated with successful match.

Birth order of a child is assigned based on the biological mother's identification number and the child's age, whereby 57 percent of children aged 7 to 17 years were matched to their biological mothers. Among those not matched to their mother, in 48% of the cases the mother was deceased, with the remaining 52% mother's identification code missing. The children who are not matched to mothers are excluded from the analysis sample, and difference between matched children and unmatched children is shown in the Appendix Table 2.

2. Empirical Strategy

As shown in the theoretical framework, household faces the different budget constraints in each period and decides which child is sent to school. Under the binding budget and credit constraints, the latter-born children are likely to be delayed in school enrollment, since the first-born child is more likely to be sent to school due to the higher expected returns on their education at the time (lower discounting rate). Using following regression specification, I estimate probability of school enrollment by age (7-17) as a function of the birth order, and other characteristics.

$$\Pr(S_{ih}=1 \mid age_{ih}=j) = B'_{ih}\delta + X'_{ih}\beta + Z'_{h}\gamma + \varepsilon_{ih}\ ,\ \ j = 7,8..,17 \text{ ---- [Equation 1]}$$

Child's school enrollment (S_{ih}) is a function of birth order (B'), characteristics of child i (X'_{ih}), such as gender, age, and age gap between older sibling and the child,[7] household's characteristics

[7] First-born child's age gap is coded as zero.

(Z'_h), including number of children, assets, and parents' characteristics. B' is a vector of dummy variables for the second-born child, for the third-born child, and for the fourth or latter-born children, where the comparison category is the first-born child. This regression equation is stratified by age of a child i; therefore, the δ represents, conditional on the age of child (j), the difference between the child i and the first-born child in terms of probability of school enrollment. The sign of $\hat{\delta}$ is expected to vary depending on the age of the child. If latter-born children's school enrollment is delayed, $\hat{\delta}$ of latter-born child is negative and significant for young school-age children, however, as the child's age increases, $\hat{\delta}$ increase because relative schooling cost (both direct and indirect) for the earlier-born children becomes greater. In order to check whether the earlier-born children drop out of school to work more, the regressions on probability of working and hours worked are estimated using the same specification as given by Equation 1. The regressions are estimated using linear probability model (LPM) and ordinary least square (OLS).

This specification, however, may result in biased estimates if fertility and educational investment decisions are correlated. For example, parents who care more about the education of their children may decide to have fewer children in order to educate all the children equally well (Becker and Tomes, 1976). In the theoretical framework, I assumed the fertility decision is exogenous since the model is to explain the poor household's educational investment and sibling difference parsimoniously. Empirically, however, in order to avoid any potential bias,[8] I used the mother-level fixed-effect model to control for unobserved factors correlated with both fertility and educational investment.

[8] The family planning was rare in Tanzania during the study period. According to Ngallaba et al (1993), only 10 percent of women aged between 15 and 49 used any contraceptive method during 1991-1992. However, there is still a possibility of the family planning for some households; therefore, the mother fixed effect is used for robust estimation.

$$\Pr(S_{ih}=1)=B'_{ih}\delta+X'_{ih}\beta+Z'_{h}\gamma+\alpha_h+\varepsilon_{ih} \text{ --- [Equation 2]}$$

Equation 2 is estimated with the mother-level fixed effect where the data sample includes children aged 7 to 17. A set of dependent variables used to investigate the household's investment on human development of each child is: (i) the standardized years of education at each age cohort ($e_{ih,c}$); (ii) a variable indicating whether a child is currently enrolled in school or not (probability of school enrollment, $\Pr(S_{ih}=1)$); (iii) a variable indicating whether a child currently works or not (working probability, $\Pr(L_{ih}=1)$); and (iv) hours worked for past 7 days (h_{ih}). The standardized years of education variable is calculated as child i's years of education minus the mean years of education for the child i's age cohort divided by standard deviation of years of education for the age cohort ($\frac{S_{ih,c}-\overline{S}_c}{s.d_c}$). The standardized years of education is used to study whether, relative to other children of the same age, the child's education level is lower or higher depending on the order of birth. This measure is required in order to assess whether the educational attainment gap between siblings becomes narrower or wider as the children grow older. Similarly, probability of school enrollment required in order to establish which child is sent to school or not, compared to first-born child within the household. Finally, the two variables can be seen as complementary, since standardized years of education measures the cumulative educational investment directed to the child over time, while schooling probability measures the educational investment directed to the specific child at any given moment. In addition to the sibling difference in educational attainment, the sibling differences in working probability and working hours are analyzed since the relatively higher opportunity cost of education induces the sibling difference in education.

As shown in the theoretical framework, the birth order effects change over the household life-cycle. Thus, the best way to study this birth order effect over the life-cycle during childhood is to observe the schooling of the same individual until one finishes education. However, the KHDS panel interviewed the same individuals for four consecutive years and re-interviewed them 10 years later. Therefore, given the limited data availability, in the present study, I compared the birth order effects between age groups—children aged 7 to 12 years, versus those 13 to 17 years of age, using the interaction terms between the birth order variables and the dummy variable, indicating that a child is aged 13 to 17. If the educational resources shift away from the earlier-born to the latter-born children, as children grow older, the coefficients of these interaction terms are expected to be positive.

In the present study, it is assumed that the sibling difference in education stems mainly from the binding budget constraints, when households cannot evenly distribute their consumptions over time. This assumption is tested using the regression estimation stratified by asset-tercile groups. In addition, it is postulated that the birth order effect is likely to be the most pronounced for households whose income is just enough to cover the subsistence level of consumption and one or two children's education cost. For extremely poor households, little evidence of birth order effect would emerge, since the most of children in the household need to work to survive. Similarly, in rich households, most children are likely to be sent to school, thus eliminating birth order effect.

Given that there is no indication that this time-varying birth order effect on education would be canceled out by the time all siblings reach adulthood, I also analyze the sibling difference in *complete* years of education for the same children after all of them grew up and become at least 17 years old. Same specification as the previous cross-sectional analysis is used. This regression is used to briefly address which effect dominates at the end—delayed school enrollment for the latter-born children, or dropping out of the school for the earlier-born children. If the former dominates the latter, the latter-born children have significantly lower level of complete years of education compared to the earlier-born children. Finally, since thirty five percent of children were not re-interviewed again, the inverse probability weight (IPW) is estimated to correct the possible attrition bias.

IV. Results

1. Descriptive Results

Table 1 describes fertility, children's and parents' characteristics. The first panel in Table 1 provides the description for children that were aged 7 to 17 years during the survey period 1991-1994. There are 4.8 children per mother and a quarter of the sample is the first-born child. In terms of children's activity, in 1991-1994, sixty four percent of children were enrolled in school, sixty eight percent of them were working,[9] and sixteen percent were idle. The second panel in Table 1 shows the description for the same children, with the information gathered in 2004 KDHS, thereby the children surveyed in 1991-1994 are considered adults in 2004. Mean complete years of education found in 2004 are calculated as 7 years, which is equivalent to one more year of education after completion of primary education. In the 2004 sample, only the children whose information is matched to their mother's information are included. Appendix Table 2 shows that the children whose birth orders are not missing seem to be slightly more active, meaning that they were more likely to enroll in school or work, compared to the children with birth order missing. However, children with birth order missing engaged in more household work.[10] However, in this study, the model is not generalized to children without mother in the

[9] 46 percent of children were both working and schooling at the same time.
[10] Household work includes collecting water and firewood, taking care of ill household members, cleaning and cooking.

household, since parents are important decision makers who generate the sibling difference in education.

Table 1. Descriptive Statistics for key variables

Variable	
In 1991-1994	
Birth order and Fertility	
First-born (%)	25.3
Second born (%)	26.2
Third Born (%)	20.7
Fourth or Later Born (%)	28.1
Number of children	4.8
Characteristics of Child and Parents	
Schooling (%)	63.8
Working (%)	67.7
Idle (%)	16.0
Female (%)	47.9
Mother Died (%)	.
Father Died (%)	22.9
Mother Read (%)	62.5
Mother's age	40.8
Father Read (%)	85.2
Father's age	51.0
N	3899
In 2004	
Complete years of education	7.21
Std. Years of Education	0.06
Worked as laborer (%)	4.48
Worked in family farm (%)	82.5
N	1271

Note: Sample includes children aged 7 to 17 years in 1991-1994 whose information is matched with mother's information. Birth order and fertility is based on the first-wave (1991) and mapped to the latter-waves.

Table 2 describes the children's activity by birth order more in detail. On average, it is evident the latter-born children are less likely to enroll in school, and the middle-born children are more likely to work while still in school. However, it appears that latter-born children are most likely to be doing nothing. However, this discrepancy is likely to be due to the younger age for the latter-born children. Thus, to control the age effect, the sample was divided into different age groups and the activities were compared depending on the birth order.

Table 2. Children's activities by birth order and gender

	First-Born	Second-Born	Third-Born	Fourth or latter-Born
In 1991-1994				
Schooling only (%)	63.1	63.6	65.4	63.2
	(1.5)	(1.5)	(1.6)	(1.4)
Working only (%)	69.6	72.7***	68.2	60.7***
	(1.5)	(1.4)	(1.6)	(1.5)
Doing both (%)	45.2*	49.0	49.9	46.2
	(1.6)	(1.5)	(1.7)	(1.5)
Hours worked, past 7 days	9.9***	9.7***	7.8**	6.2***
	(0.4)	(0.4)	(0.3)	(0.3)
Idle (%)	12.5***	12.6***	16.2	22.3***
	(1.1)	(1.0)	(1.3)	(1.3)
Age	12.6***	12.4***	11.7	10.6***
	(0.1)	(0.1)	(0.1)	(0.1)
In 2004				
Complete years of education	7.1	7.4**	7.2	7.2
	(0.2)	(0.2)	(0.2)	(0.1)
Worked in 1991-1994 (%)	83.0*	88.5***	82.2	78.5
	(2.0)	(1.8)	(2.3)	(2.3)
Age	24.7***	24.4***	23.3	21.7***
	(0.2)	(0.2)	(0.2)	(0.2)

Note: Standard errors for the comparison between siblings are in the parentheses. The mean difference is statistically significant at 1 % level (***), at 5 % level (**), and at 10 % level (*).

The Figure 1 shows children's activity by age group. The first graph represents school enrollment rate of each birth order in relation to age group. In the younger age group (age 7-8), the probability of school enrollment for the first-born child is higher than for the latter-born children. As children's age increases, the probability for the third or latter-born children to attend school increases at a higher rate than it does for the earlier-born children. Around the age of 11 to 12, the latter-born children's probability of enrolling to school becomes higher, compared to that associated with the earlier-born children, and this trend continues until the end of school-age (age 17). This may indicate that the latter-born children's schooling is delayed; however, this pattern can also be attributed to fertility, whereby children with many siblings are likely not to go to school. This issue will be further explored in the regression analysis in the next section. The second and the third graphs in Figure 1 show the working probability and weekly working hours of each birth order by age group. It is evident that there is little difference in working probability between siblings for younger age group (age 7-8), as children are still considered too young to work. However, from age 7-8 to age 9-10, the working probability increases dramatically, after which the increase becomes more gradual. It seems to indicate some gaps between siblings, yet the pattern is neither clear nor significant. On the other hand, while work intensity (working hours) increases slowly as children's age increases, the earlier-born children work the most regardless of their age. However, this again is confounded with the fertility, the number of siblings who can work.

Figure 1. Children's activities by birth order in relation to age

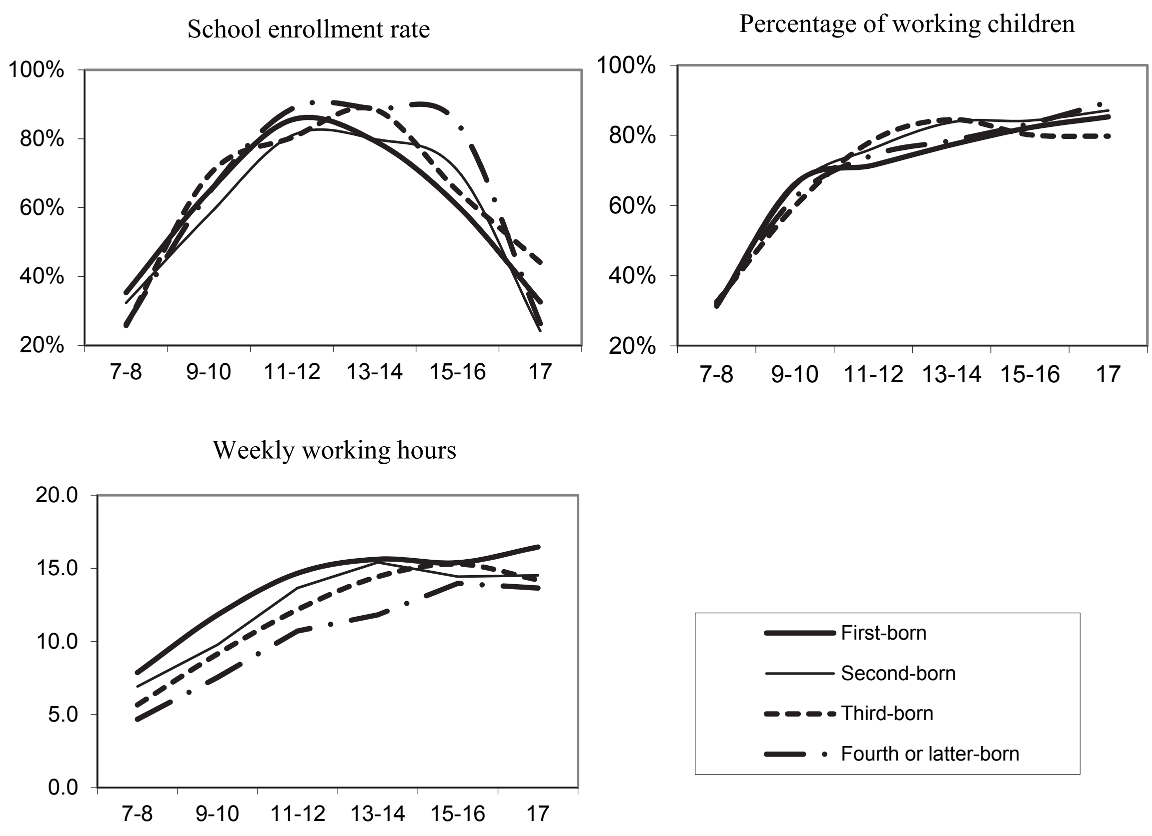
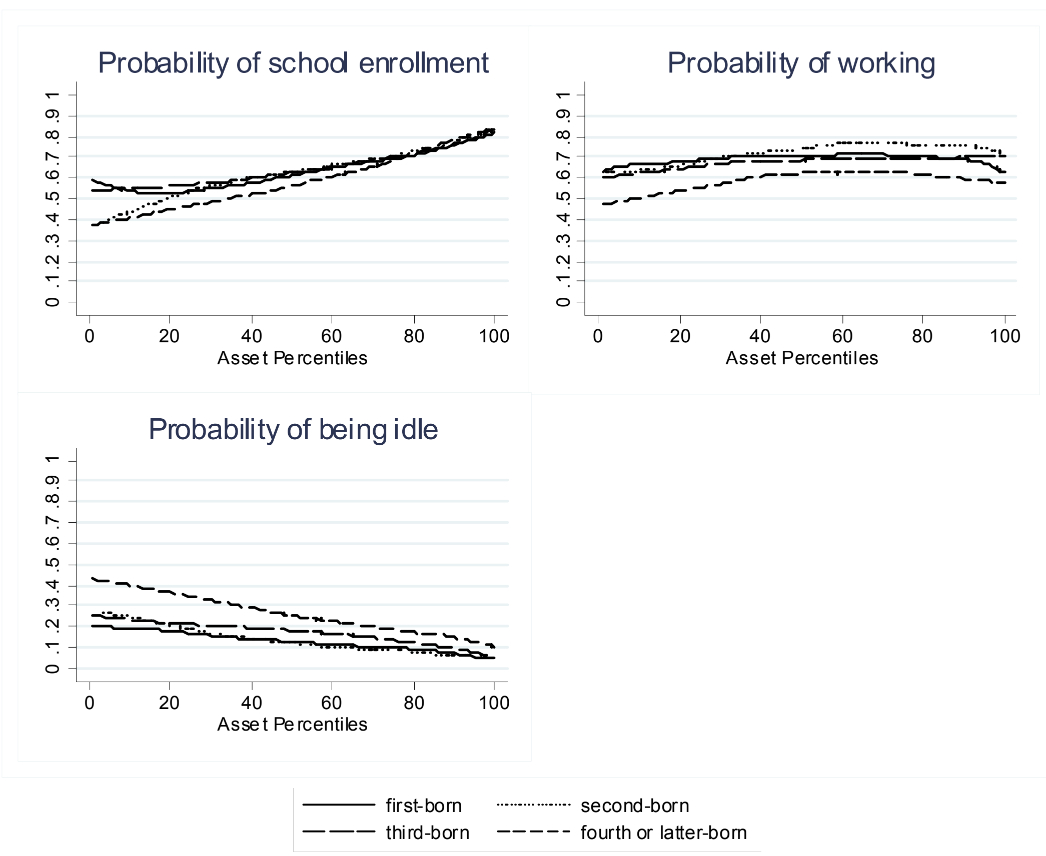


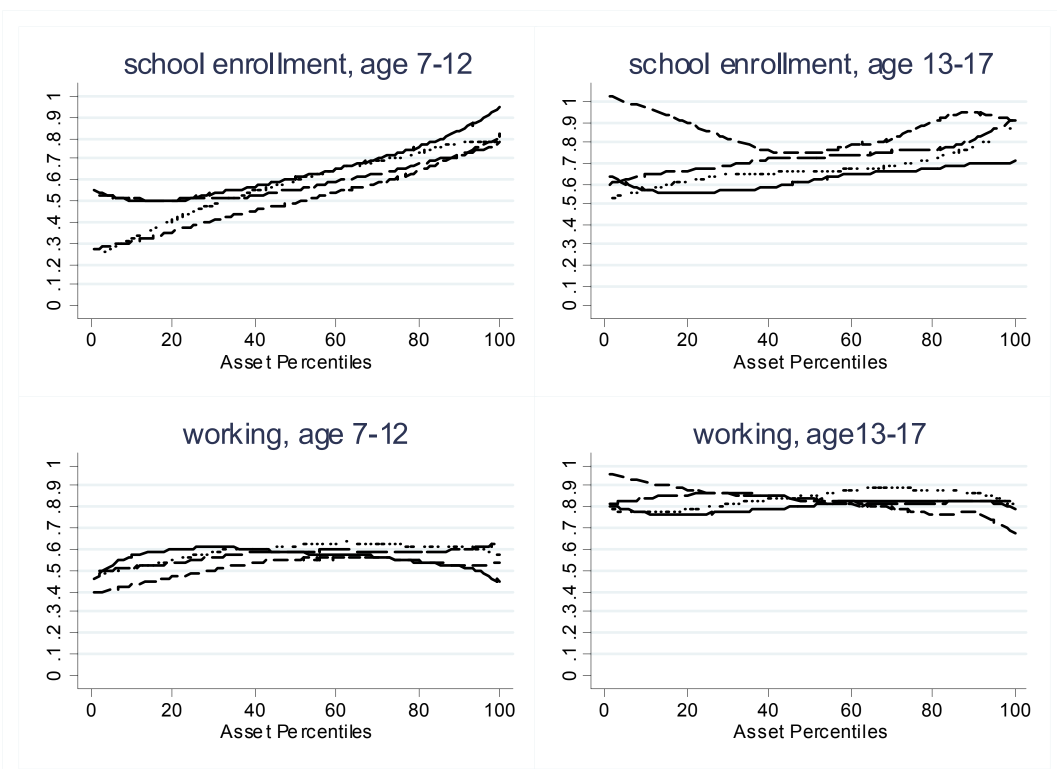
Figure 2 describes probability of school enrollment, probability of working, and probability of being idle in relation to asset level. Overall, the probability of school enrollment increases as asset level increases, while curve showing the probability of working is rather flat across the asset level. Increase in the probability of school enrollment results from the decrease in probability of being idle as asset increases, which may indicate that children work regardless of the wealth of household. However, in the presence of binding budget constraints, children are not sent to school. Similarly, for households in lower asset percentiles, marked sibling difference in the probability of school enrollment is evident. For poor households, latter-born children are less likely to enroll in school, and this gap becomes narrower as the asset increases. In terms of the probability of working, latter-born children are always less likely to work regardless of the asset level.

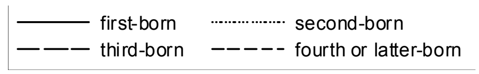
Figure 2. Children's activities by birth order in relation to household's asset



As discussed in the previous section, this relationship between children's activities and birth order may differ by the age of children. Figure 3 describes the relationship between children's activities and household's asset level by the birth order and children's age group (aged 7-12 and 13-17). It is evident that the probability of school enrollment increases with higher asset level for children aged 7 to 12 years, which is not the case for children age 13 to 17. Furthermore, amongst younger children (aged 7-12), the latter-born children are much less likely to enroll in school, whereas, in the older group (aged 13-17), the trend is reversed (latter-born children are most likely to enroll in school). On the other hand, no clear relationship between working and household's asset level emerges for either age group, whilst working probability of old children is much higher, compared to young children.

Figure 3. Children's activities by birth order and age group in relation to household's asset

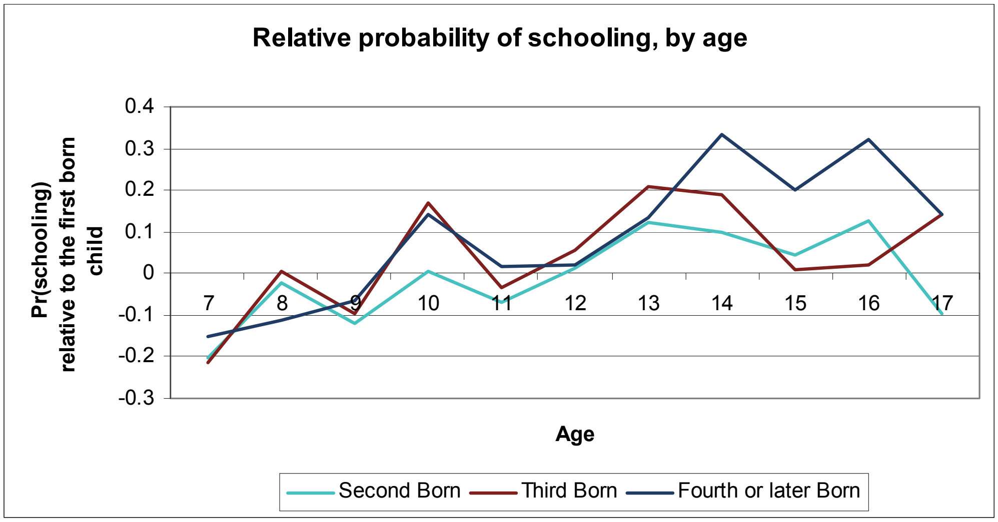




2. Regression Analysis Results

In this section, the birth order effects on school enrollment and working are analyzed parametrically. First, the regression is stratified by child's age in order to assess whether the birth order effect changes as children's age increases. Figure 4 depicts the birth order effect on school enrollment by age. It shows that, compared to the first-born children, the latter-born children are much less likely to enroll to school at the age of 7. Moreover, the second-born and the third-born children are about 20 percent less likely to start education and the differences are statistically significant. Similarly, the fourth or latter-born children are about 15 percent less likely to enroll in school; however, the difference is not statistically significant. As children's age increases, the gap between the first-born child and the latter-born children narrows, and at around age of 10, the birth order effect becomes reversed, whereby the latter-born children become more likely to enroll in school. This result is consistent with the findings of the earlier non-parametric analysis. The latter-born children are often delayed in schooling in young ages, compared to the first-born children. However, as children grow older, the latter-born children are more likely to go to school than the first-born children are, and the effects are more pronounced and statistically more significant, especially for the fourth or latter-born children.

Figure 4. Difference in the probability of school enrollment between the first-born child and the latter-born children ($\hat{\delta}$), by age

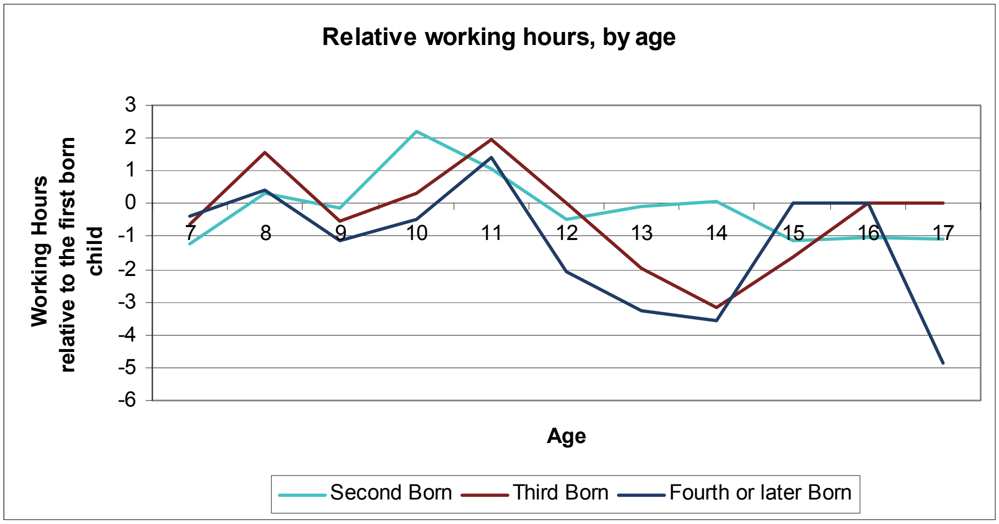


Note: $\hat{\delta}$ is based on linear probability model: $\Pr(S_{ih} = 1 \mid age_{ih} = j) = B'_{ih}\delta + X'_{ih}\beta + Z'_{h}\gamma + \varepsilon_{ih}$
Dependent variable is whether or not the child is enrolled in school and the regression is stratified by age. The covariates included in the regression are child's gender and age, parent's literacy, age, the number of children, birth spacing, employment status, and the household's asset. The regression result is shown in Appendix Table 3.

Figure 5 is analogous to Figure 4, with weekly working hours[11] as the dependent variable. In this respect, for young children, there is little sibling difference; however, amongst older children, the first born-children work more intensely than the latter-born children do. This may reflect the findings that the latter-born children are more likely to enroll in school at the older age (12-17).

[11] Regression result for the probability of working is shown in Appendix Table 4.

Figure 5. Difference in the working hours between the first-born child and the latter-born children, by age



Note: Dependent variable is weekly working hours, and the regression is stratified by age. The covariates included in the regression are child's gender and age, parent's literacy, age, the number of children, birth spacing, employment status, and the household's asset. The regression result is shown in Appendix Table 4.

When fertility decision and human development investment decision are correlated, the previous results can be biased. For example, when households make fertility decision, they consider the quality and quantity trade-offs, whereby parents that care more about children's education tend to have fewer children in order to ensure that all children can be educated equally well. Thus, in order to avoid the potential bias that arises from this effect, mother-level fixed-effect model is employed.

Table 3 shows the birth order effect on school enrollment and working outcomes, with mother fixed effect. Since years of education is a function of age, as is the birth order, age-adjusted years of education (standardized years of education) is used to compare siblings and it is shown in the first column in Table 3. The findings indicate that latter-born children tend to acquire lower standardized number of years of education compared to the first-born child and the magnitude of this negative effect increases as birth order increases, while the latter-born children are more likely to enroll in school. The discrepancy between the two outcomes (standardized years of schooling and probability of school enrollment) may be explained by the delay in onset of schooling for the latter-born children at young age even though they are more likely to enroll in school at older age compared to the first-born child. The results of probability of working and hours worked still show that the second-born child works most likely and most intensely.

Table 3. Mother-level fixed-effect

	Std. yrs of education	Enrollment	Working	Hours worked
Second-born	-0.043	0.046	0.059***	0.448
	(0.060)	(0.029)	(0.023)	(0.541)
Third-born	-0.310***	0.116***	0.053	-0.812
	(0.091)	(0.041)	(0.033)	(0.777)
Fourth or latter-born	-0.624***	0.159***	0.035	-0.765
	(0.130)	(0.058)	(0.047)	(1.105)
N	2829	3899	3899	3899

Note: Covariates included in the regression are child's gender, age, birth spacing, father's age, literacy, and employment status. Robust standard errors are shown in the parentheses. The estimate is statistically significant at 1 % level (***), at 5 % level (**), and at 10 % level (*).

As described in the theoretical framework and shown in the regression analysis earlier in the section, birth order effects can vary depending on the age of a child in question, as well as that of his or her siblings. The regressions stratified by each age are, however, not possible when mother level fixed effect model applied. Thus, in order to show how the age of child affects the birth order effect, the set of interaction terms between birth order and a variable indicating that child is age between 13 and 17 years old (secondary school-age) is used. Thus, the interaction term indicates the birth order effect difference between young children (age 7-12) and old children (age 13-17). If the birth order effect on school enrollment is negative when children are young, whereas, as children grow older, the negative effect decreases, the interaction term should be positive. This is clearly shown in the first and the second columns in Table 4. When children are aged 7 to 12, the standardized years of education for the latter-born children are much lower than that for the earlier-born children. Compared to the first-born child, the years of education is 0.21, 0.66, and 1.1 standard deviation lower for the second-, third- and fourth or latter-born children respectively. However, the birth order effect is less negative for children aged 13-17, as indicated by the positive signs for the interaction terms. This may indicate that delaying school enrollment for the latter-born children is compensated in older age, although their standardized educational attainments are still lower compared to those of the earlier-born children. This also indicates that the earlier-born children stop their education after completing level of education (e.g. primary education), with the school enrollment showing similar pattern. For children aged 7-12, compared to the first-born child, the probability of school enrollment is 24.8, 33.1, and 30 percent lower for the second-, third- and fourth or latter-born children, respectively. Again, the birth order effect on school enrollment is less negative for children aged 13-17 compared to that associated with the children aged 7-12. Moreover, amongst young children, the latter-born children are much more likely being idle than the first-born child, indicating that their schooling is not delayed because of their work commitments. In terms of probability of working, the latter-born children are less likely to work when young, even though in this age group (7-12), the birth order effects are small and not precisely estimated. However, positive birth order effect on weekly working hours is evident for young children, becoming less positive as children grow older.

Table 4. Birth order interacted with secondary schooling age dummy (age 13~16 years old), mother level fixed effect model

	Std. yrs of education	Enrollment	Idle	Working	Hours worked
Second-born	-0.211*	-0.248***	0.088**	-0.019	1.378**
	(0.110)	(0.041)	(0.035)	(0.035)	(0.688)
Third-born	-0.658***	-0.331***	0.127**	-0.065	0.945
	(0.143)	(0.057)	(0.050)	(0.052)	(1.068)
Fourth or Latter-born	-1.058***	-0.295***	0.112*	-0.094	0.634
	(0.168)	(0.077)	(0.065)	(0.067)	(1.410)
Second-born × Aged 13-17	0.095	0.334***	-0.165***	0.091**	-0.881
	(0.123)	(0.053)	(0.039)	(0.042)	(1.004)
Third-born ×Aged 13-17	0.288*	0.563***	-0.257***	0.139***	-2.660**
	(0.154)	(0.062)	(0.047)	(0.052)	(1.215)
Fourth or Latter-born × Aged 13-17	0.500***	0.650***	-0.291***	0.181***	-2.087*
	(0.146)	(0.058)	(0.046)	(0.052)	(1.163)
Aged 13-17	-0.305**	-0.571***	0.400***	-0.271***	-0.735
	(0.131)	(0.048)	(0.040)	(0.042)	(0.900)
Age	-0.014	0.051***	-0.081***	0.076***	1.522***
	(0.018)	(0.008)	(0.007)	(0.007)	(0.145)
N	2829	3899	3899	3899	3899

Note: The sample for the standardized years of schooling regression does not include children attending non-formal school because there is no grade attached to this school hence not able to calculate the number of years. The results excluding the children attending non-formal school for all the regressions are shown in Appendix Table 5. Covariates included in the regression are aged 13-17 dummy, child's gender, age, birth spacing, father's age, literacy, and employment status. Robust standard errors are shown in the parentheses (Appendix Table 6).

The main reason for the sibling difference in school enrollment is that household cannot afford to send all children to school. However, the birth order effect in relation to household income can be non-linear, whereby in extremely poor households, most or all the children get little education. In contrast, households with less biding budget constraint may make a decision to send one or two children to school at a time. Finally, rich households can send all of the children to school, hence, little sibling difference is found in this group.

In order to interpret the study findings accurately, it is necessary to know the poverty rate of the analysis sample. Fifty four percent of households lived under the poverty line in rural Tanzania in 1991, consuming up to 2000 calories per day (Sarris and Tinios, 1990). Based on this regional background, we expect the strongest birth order effect for the households at around the poverty line, and less so for the very poor and non-poor households. Table 5 shows the birth order effect by asset tercile. For the bottom sixty percent of households in asset distribution, for children aged 7-12 years, there is a negative birth order effect on the standardized years of education and school enrollment, while the birth order effects become less negative for children aged 13-17. The effects are greater and stronger for the households in between 30^{th} and 60^{th} percentiles. Finally, for the top thirty percent of households, there are still negative birth order effects on the standardized years of education, however, the effects are smaller and the interaction terms are not significant. Birth order effects on working hours are also the strongest for the households in the second asset-tercile. The latter-born children work more in the earlier age while the effect becomes less for older children. There is no birth order effect on working for the wealthiest group, whereas, for the poorest group, it is evident in terms of working probability, but not in the number of working hours.

Table 5. Mother Fixed Effect: Birth Order by Asset Tercile

	std. yrs of education	Enrollment	Working	Working Hours
Asset: First tercile				
Second-born	-0.532	-0.402***	-0.110	0.773
	(0.325)	(0.095)	(0.075)	(1.556)
Third-born	-0.856*	-0.428***	-0.262**	-2.581
	(0.442)	(0.134)	(0.106)	(2.186)
Fourth or Latter-born	-1.328**	-0.555***	-0.378***	-3.310
	(0.544)	(0.167)	(0.132)	(2.733)
Second-born × Aged 13-17	0.674**	0.408***	0.162*	0.314
	(0.342)	(0.112)	(0.089)	(1.836)
Third-born ×Aged 13-17	0.720*	0.459***	0.228**	1.691
	(0.429)	(0.143)	(0.113)	(2.337)
Fourth or Latter-born × Aged 13-17	0.784*	0.631***	0.371***	2.857
	(0.449)	(0.161)	(0.127)	(2.631)
Asset: Second tercile				
Second-born	-0.512**	-0.285***	-0.032	3.013**
	(0.210)	(0.081)	(0.064)	(1.502)
Third-born	-1.063***	-0.440***	-0.035	3.201
	(0.281)	(0.106)	(0.083)	(1.964)
Fourth or Latter-born	-1.626***	-0.498***	-0.043	3.871
	(0.331)	(0.129)	(0.101)	(2.391)
Second-born × Aged 13-17	0.409*	0.379***	0.151**	-3.339*
	(0.228)	(0.097)	(0.076)	(1.788)
Third-born × Aged 13-17	0.661**	0.709***	0.232**	-4.623**
	(0.276)	(0.116)	(0.091)	(2.145)
Fourth or Latter-born × Aged 13-17	0.897***	0.931***	0.222**	-6.506***
	(0.278)	(0.121)	(0.095)	(2.249)

(Continued.)

	std. yrs of education	Enrollment	Working	Working Hours
Asset: Third tercile				
Second-born	0.060	-0.134*	0.042	-0.068
	(0.153)	(0.069)	(0.059)	(1.489)
Third-born	-0.427**	-0.192**	-0.008	0.281
	(0.188)	(0.085)	(0.074)	(1.845)
Fourth or Latter-born	-0.715***	0.008	-0.022	-1.010
	(0.233)	(0.106)	(0.092)	(2.302)
Second-born × Aged 13-17	-0.350*	0.261***	-0.006	0.815
	(0.183)	(0.085)	(0.073)	(1.838)
Third-born ×Aged 13-17	-0.090	0.509***	0.018	-2.783
	(0.206)	(0.096)	(0.083)	(2.089)
Fourth or Latter-born ×Aged 13-17	0.188	0.451***	0.068	-0.434
	(0.197)	(0.094)	(0.081)	(2.029)

Note: Covariates included in the regression are aged 13-17 dummy, child's gender, age, birth spacing, father's age, literacy, and employment status. Robust standard errors are shown in the parentheses.

Next, using KHDS in 2004, I examine the birth order effect on complete years of education when the children in 1991-1994 become at least 17 years old.[12] The question that this analysis attempts to answer is—which effect is more significant, delaying school enrollment for the latter-born children, or dropping out of school for the earlier-born children? Table 6 provides the answers. Compared to the first-born child, years of education is 0.29, 0.49, and 0.70 standard deviation lower for the second-, third- and fourth or latter-born children. This implies the latter-born children are disadvantaged because of delayed school enrollment. The regressions of the second panel in Table 6 are estimated using inverse probability weight to correct non-random matching between childhood sample (1991-1994) and adult sample (2004), indicating that the results are robust.

[12] The youngest age cohort is 17 years old in 2004 (7 years old in 1994).

Table 6. Birth Order and years of education in 2004, mother-level fixed-effect

			Sample correction, IPW	
	Years of education	Std. years of education	Years of education	Std. years of education
Second-born	-0.668*	-0.289**	-0.731*	-0.409**
	(0.373)	(0.135)	(0.442)	(0.190)
Third-born	-1.031**	-0.493***	-1.104*	-0.619**
	(0.492)	(0.179)	(0.591)	(0.243)
Fourth or latter-born	-1.413*	-0.703***	-1.521*	-0.854**
	(0.727)	(0.261)	(0.841)	(0.344)

Note: Covariates included in the regression but not shown are child's gender, age, working status in 1991-1994, birth spacing, and father's characteristics in 1991-1994. Regression result without mother-level fixed-effect (OLS) is reported in Appendix Table 7.[13]

As shown in Table 5, the birth order effect is most pronounced for households at around the poverty line (2nd asset tercile group). Table 7 describes the birth order effects on completed years of education by asset tercile group.[14] The asset is measured in 1991-1994, and the years of education based on 2004 data. The findings suggest no significant birth effects on years of education for children in bottom 60 percent in terms of asset distribution. However, it seems that, the richer the households, the more negative birth order effect is on completed years of education. For the poorest children, the birth order effects are marginally positive, for the second poorest, the birth order effects are negative but not significant, and for the wealthiest, the birth order effects are negative and statistically significant. This result reflects the earlier findings in Table 5. For the wealthiest group, the negative birth order effects persist even for older children, and this may be due to the fact that the earlier-born children do not need to drop out of school while the latter-born children still delay school enrollment. Furthermore, these findings indicate that the results

[13] The regressions without mother-level fixed-effects result in under-estimation of birth order effects. This may be due to the correlation between fertility decision and educational investment, or correlation between household's income and birth order effect when there is a measurement error in household's income. I used mean asset level in 1991-1994 to proxy household's income during the childhood. In addition, the number of children (siblings) is included in the regression; however, this variable is based on information in 1991-1994, and there is possibility of measurement error.

[14] It was calculated based on the mean of asset percentiles in 1991-1994.

reported in Table 6 are mainly due to the negative birth order effect for the children from the highest asset tercile.

Table 7. Mother Fixed Effect: Birth Order and Complete years of education, by asset

	Years of education			Std. yrs of education		
	Asset: 1st Tercile	Asset: 2nd Tercile	Asset: 3rd Tercile	Asset: 1st Tercile	Asset: 2nd Tercile	Asset: 3rd Tercile
Second-born	-0.073	0.184	-1.277**	-0.044	-0.052	-0.607**
	(0.620)	(0.632)	(0.641)	(0.274)	(0.266)	(0.287)
Third-born	0.488	-0.112	-2.082***	0.237	-0.258	-0.955***
	(0.777)	(0.862)	(0.660)	(0.339)	(0.351)	(0.298)
Fourth or latter-born	0.729	-0.244	-3.154***	0.343	-0.489	-1.410***
	(0.893)	(1.351)	(1.062)	(0.385)	(0.535)	(0.479)

Note: Covariates included in the regression but not shown are child's gender, age, working status in 1991-1994, birth spacing, and father's characteristics in 1991-1994.

V. Conclusion and Discussion

The theoretical framework employed in this study postulates that the birth order effect on education varies over time, as household faces multi-periods utility maximization problem depending on the discounted returns to education of children and time varying educational costs. The findings suggest that, under the binding budget and credit constraints, the latter-born child is more likely to delay starting school due to the higher discounting rate for the returns to education. Moreover, the first-born child is more likely to drop out of school due to the higher opportunity cost of schooling when he or she becomes old enough to earn higher wage, compared to younger sibling.

Using the children sample in rural Tanzania, in 1991-1994 (KHDS), I show that the probability of school enrollment for the latter born children relative to the first born child's is lower for young school-age children while the gap decreases as child's age increases, suggesting delaying in school enrollment for the latter-born children while narrowing educational gap in the later years. However, the working probability for the earlier-born children relative to the latter-born children increases as their age increases. Decreasing relative probability of schooling and increasing relative probability of working imply that the first-born children drop out of school in the later years, as they are able to earn living, bringing additional income to their households. This finding is robust when mother-level fixed-effect model is applied. Moreover, this effect is most pronounced for households at around the poverty line, confirming that the binding budget and credit constraints are driving the birth order effect change. Since the birth order effect diminishes as the age increases, we may expect the negative birth order effects on education in the earlier years are canceled out in the later years. Using the same sample population, but relying on children's adulthood information on educational attainments, I find there is little birth order effect on complete years of education for poor households. However, positive birth order effect is evident for the non-poor households, which is consistent with the findings from the childhood sample, which is that the first-born children's relative probability of schooling remains higher overall. This may imply that they do not drop out of school as the latter born children's school enrollment is delayed.

This finding has policy implications for intervening in household educational decisions. Theoretically and empirically, in-kind educational subsidy, such as conditional cash transfer program, it is proven to be effective, and it is especially so when it targets to the children most vulnerable to drop out of school (Caucutt and Kumar, 2006; Schultz, 2004; Schady and Araujo, 2008; de Janvry et al, 2006). However, there is evidence in support of the fact that the potential displacement effect generated by foregone income of the eligible child is not negligible (Ferreira et al., 2009). The findings reported in this paper suggest that younger siblings are typically transitioning into schooling at a later age, and this may be partly facilitated by the earnings of older siblings. Therefore, if the conditional cash amount is not enough to cover both direct and indirect cost of the eligible child, the latter-born children may stay out of school for longer. Thus, in order to counteract this effect, the program can be modified based on the eligible child's sibling age structure and schooling status. Furthermore, most programs and studies have focused on preventing children from dropping out of school, whereas there are few studies addressing the need and means for mitigating delays in school enrollment of the younger siblings, in particular when due to low income, the household's resources are directed to the older children.

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Appendix

Appendix Table 1. Matching Probability

Matched	Coef.	Std. Err.
Worked as laborer	0.162	(0.109)
Worked at farm	0.910***	(0.102)
Second-born	-0.074	(0.198)
Third or latter-born	0.416	(0.263)
Age	-0.030***	(0.003)
Female	-0.046	(0.078)
Average Asset	-0.074	(0.095)
Average Land	0.284***	(0.084)
#HH mem (female 0~5 yrs)	0.198***	(0.067)
#HH mem (male 0~5 yrs)	0.010	(0.065)
#HH mem (female 7~14 yrs)	0.038	(0.056)
#HH mem (male 7~14 yrs)	0.062	(0.052)
#HH mem (female 15~18 yrs)	0.127	(0.090)
#HH mem (male 15~18 yrs)	0.047	(0.091)
#HH mem (female 19~60 yrs)	0.060	(0.056)
#HH mem (male 19~60 yrs)	-0.173***	(0.065)
#HH mem (60+ yrs)	0.048	(0.038)
Mother, self employed	0.125	(0.364)
Father, self employed	-0.013	(0.225)
Mother, farm worker	0.464**	(0.208)
Father, farm worker	0.339***	(0.130)
Mother, read	-0.103	(0.192)
Father, read	-0.065	(0.240)
Mother, age	0.002	(0.005)
Father, age	0.000	(0.004)
Mother, died	-0.100	(0.097)
Father, died	0.248**	(0.113)
Birth order missing	-0.362	(0.273)
Constant	-0.116	(0.326)

Appendix Table 2. Mother's information

Variable	Sample A: Children matched to mother	Sample B: Children unmatched to mother
1991~1994 Sample		
Birth order and Fertility		
First-born (%)	25.3	
Second-born	26.2	
Third-born	20.7	
Fourth or Latter-born	28.1	
Number of children	4.8	
Characteristics of Child and Parents		
Schooling	63.8	60.4
Working	67.7	65.4
Idle	16.0	17.6
Female	47.9	51.6
Mother Died	.	46.4
Father Died	22.9	32.9
Mother Read	62.5	.
Mother's age	40.8	
Father Read	85.2	85.8
Father's age	51.0	51.6
Value of Asset (median)	176,850	213,650
Value of Land (median)	266,667	200,000
N	3899	2927
2004 sample		
Complete years of education	7.2	7.0
Std. Years of Education	0.1	-0.1
Worked as laborer (%)	4.5	3.6
Worked in family farm (%)	82.5	74.8
N	1271	1218

Appendix Table 3. Probability of school enrollment by age, OLS

	Age										
	7	8	9	10	11	12	13	14	15	16	17
Second-born	-0.203**	-0.023	-0.120	0.005	-0.070	0.013	0.124	0.098	0.044	0.127	-0.096
	(0.096)	(0.119)	(0.134)	(0.132)	(0.103)	(0.101)	(0.093)	(0.083)	(0.109)	(0.099)	(0.124)
Third-born	-0.213*	0.004	-0.098	0.171	-0.033	0.054	0.207*	0.187**	0.007	0.021	0.140
	(0.110)	(0.136)	(0.146)	(0.126)	(0.090)	(0.119)	(0.118)	(0.084)	(0.112)	(0.123)	(0.139)
Fourth or latter-born	-0.150	-0.114	-0.067	0.141	0.016	0.021	0.136	0.333***	0.200*	0.321**	0.143
	(0.158)	(0.150)	(0.191)	(0.133)	(0.128)	(0.132)	(0.111)	(0.092)	(0.102)	(0.121)	(0.192)
N	303	326	304	302	276	341	345	313	294	268	250

Note: Dependent variable is schooling or not and the regression is stratified by age. Covariates include a child's gender and age, parent's literacy, age, the number of children, birth spacing, and employment status, and the household's asset. Standard errors are clustered at mother level.

Appendix Table 4. Working by age, OLS

	Age										
	7	8	9	10	11	12	13	14	15	16	17
Probability of Working											
Second-born	-0.128	0.165	0.096	0.198*	0.327***	-0.075	-0.068	0.102	-0.104	0.033	0.046
	(0.134)	(0.140)	(0.109)	(0.113)	(0.120)	(0.104)	(0.099)	(0.090)	(0.084)	(0.058)	(0.068)
Third-born	-0.077	0.223	0.035	0.068	0.349***	-0.028	-0.095	0.123	-0.153*	-0.086	0.005
	(0.114)	(0.138)	(0.129)	(0.139)	(0.117)	(0.110)	(0.113)	(0.081)	(0.085)	(0.079)	(0.082)
Fourth or latter-born	-0.025	0.270	0.133	0.137	0.450***	-0.127	-0.159	0.077	-0.092	-0.160	-0.009
	(0.159)	(0.169)	(0.161)	(0.137)	(0.143)	(0.134)	(0.130)	(0.117)	(0.089)	(0.096)	(0.134)
Working hours (unconditional)											
Second-born	-1.239	0.313	-0.112	2.194	1.039	-0.465	-0.070	0.082	-1.123	-1.024	-1.084
	(1.872)	(2.536)	(2.033)	(1.910)	(2.259)	(2.345)	(2.605)	(2.005)	(2.440)	(2.151)	(3.772)
Third-born	-0.605	1.558	-0.537	0.309	1.978	-3.621*	-1.973	-3.147	-1.638	-3.648*	-8.632**
	(1.844)	(2.379)	(2.144)	(2.391)	(1.995)	(2.014)	(2.400)	(2.241)	(2.311)	(2.087)	(3.938)
Fourth or latter-born	-0.404	0.431	-1.111	-0.477	1.391	-2.083	-3.253	-3.580	-4.274*	-6.930**	-4.846
	(2.428)	(3.082)	(2.748)	(2.550)	(2.772)	(2.666)	(2.904)	(2.682)	(2.417)	(3.044)	(5.039)
N	303	326	304	302	276	341	345	313	294	268	250

Note: Dependent variables are whether or not child works and weekly working hours. The regression is stratified by age. The covariates included in the regression are child's gender and age, parent's literacy, age, the number of children, birth spacing, employment status, and the household's asset.

Appendix Table 5. Mother Fixed Effect, excluding children attending non-formal school

	Std. yrs of education	Enrollment	Idle	Working	Hours worked
Second-born	-0.211*	-0.202***	0.027***	-0.012	2.308***
	(0.110)	(0.019)	(0.010)	(0.040)	(0.763)
Third-born	-0.658***	-0.224***	0.030	0.001	2.112*
	(0.143)	(0.039)	(0.022)	(0.063)	(1.139)
Fourth or Latter-born	-1.058***	-0.235***	0.066*	-0.075	2.148
	(0.168)	(0.059)	(0.035)	(0.084)	(1.565)
Second-born × Aged 13-17	0.095	0.257***	-0.037**	0.050	-1.963*
	(0.123)	(0.036)	(0.016)	(0.046)	(1.169)
Third-born ×Aged 13-17	0.288*	0.337***	-0.015	0.016	-3.525***
	(0.154)	(0.043)	(0.018)	(0.060)	(1.334)
Fourth or Latter-born × Aged 13-17	0.500***	0.421***	-0.035*	0.054	-3.954***
	(0.146)	(0.035)	(0.018)	(0.060)	(1.156)
Aged 13-17	-0.305**	-0.118***	0.010	-0.085*	-0.026
	(0.131)	(0.027)	(0.013)	(0.049)	(0.905)
Age	-0.014	-0.085***	0.012**	0.034***	1.581***
	(0.018)	(0.008)	(0.005)	(0.008)	(0.197)
Female	0.192***	-0.026	0.006	-0.051***	-1.288***
	(0.040)	(0.016)	(0.006)	(0.018)	(0.449)
Father Read	0.215	0.133	0.083**	-0.306	11.031**
	(0.849)	(0.199)	(0.039)	(0.342)	(4.639)
Father's Age	-0.004	0.000	-0.001*	0.001	-0.216***
	(0.012)	(0.003)	(0.001)	(0.007)	(0.070)
Father not alive	0.172	-0.106	0.013	-0.043	0.340
	(0.203)	(0.088)	(0.028)	(0.039)	(2.146)
Constant	0.650**	2.004***	-0.170**	0.581***	-10.144***
	(0.309)	(0.124)	(0.077)	(0.146)	(3.190)
N	2829	2829	2829	2829	2829

Appendix Table 6. Mother Fixed Effect, excluding children attending non-formal school

	Std. yrs of education	Enrollment	Idle	Working	Hours worked
Second-born	-0.211*	-0.248***	0.088**	-0.019	1.378**
	(0.110)	(0.041)	(0.035)	(0.035)	(0.688)
Third-born	-0.658***	-0.331***	0.127**	-0.065	0.945
	(0.143)	(0.057)	(0.050)	(0.052)	(1.068)
Fourth or Latter-born	-1.058***	-0.295***	0.112*	-0.094	0.634
	(0.168)	(0.077)	(0.065)	(0.067)	(1.410)
Second-born × Aged 13-17	0.095	0.334***	-0.165***	0.091**	-0.881
	(0.123)	(0.053)	(0.039)	(0.042)	(1.004)
Third-born ×Aged 13-17	0.288*	0.563***	-0.257***	0.139***	-2.660**
	(0.154)	(0.062)	(0.047)	(0.052)	(1.215)
Fourth or Latter-born × Aged 13-17	0.500***	0.650***	-0.291***	0.181***	-2.087*
	(0.146)	(0.058)	(0.046)	(0.052)	(1.163)
Aged 13-17	-0.305**	-0.571***	0.400***	-0.271***	-0.735
	(0.131)	(0.048)	(0.040)	(0.042)	(0.900)
Age	-0.014	0.051***	-0.081***	0.076***	1.522***
	(0.018)	(0.008)	(0.007)	(0.007)	(0.145)
Female	0.192***	-0.037*	0.051***	-0.064***	-1.481***
	(0.040)	(0.019)	(0.013)	(0.016)	(0.389)
Father Read	0.215	0.577**	-0.121	0.324	9.071***
	(0.849)	(0.291)	(0.180)	(0.218)	(3.021)
Father's Age	-0.004	-0.007	0.001	-0.007**	-0.180***
	(0.012)	(0.004)	(0.002)	(0.004)	(0.055)
Father not alive	0.172	0.058	-0.071	-0.025	-0.681
	(0.203)	(0.106)	(0.074)	(0.058)	(1.746)
Constant	0.650**	0.261*	0.959***	0.005	-7.614***
	(0.309)	(0.140)	(0.117)	(0.116)	(2.470)
N	2829	3899	3899	3899	3899

Appendix Table 7. Years of education, OLS and FE

	Years of education		Std. years of education	
	OLS	FE	OLS	FE
Second-born	0.127	-0.668*	0.019	-0.289**
	(0.326)	(0.373)	(0.141)	(0.135)
Third-born	-0.061	-1.031**	-0.061	-0.493***
	(0.344)	(0.492)	(0.150)	(0.179)
Fourth or latter-born	-0.229	-1.413*	-0.159	-0.703***
	(0.409)	(0.727)	(0.178)	(0.261)
Female	0.097	-0.142	0.045	-0.052
	(0.177)	(0.214)	(0.077)	(0.094)
Age	0.023	-0.078	-0.004	-0.059**
	(0.032)	(0.070)	(0.013)	(0.024)
Worked in 1991-1994	0.112	-0.613	0.096	-0.142
	(0.335)	(0.447)	(0.136)	(0.174)
2nd asset tercile	0.828***		0.379***	
	(0.208)		(0.091)	
3rd asset tercile	1.412***		0.629***	
	(0.258)		(0.113)	
Number of children	0.056		0.029	
	(0.068)		(0.029)	
Birth spacing	0.033	0.049	0.019	
	(0.061)	(0.056)	(0.027)	
Non-farm self-employed, father	0.884	-4.365***	0.447	-1.966***
	(0.785)	(1.070)	(0.347)	(0.458)
Farm self-employed, father	-0.008	2.999**	0.019	1.265*
	(0.303)	(1.465)	(0.130)	(0.680)
Read, father	0.514	0.378	0.248*	0.211
	(0.312)	(1.790)	(0.136)	(0.751)
Age, father	-0.017***	0.039	-0.007***	0.014
	(0.006)	(0.055)	(0.003)	(0.024)
Died, father	-0.083	-1.743	-0.038	-0.695
	(0.350)	(1.057)	(0.151)	(0.456)
Constant	5.712***	8.915***	-0.366	1.404
	(0.790)	(2.411)	(0.320)	(0.979)
N	638	638	637	637

Chapter 2. The Effect of Child Shadow Wages on the Child Labor Supply and Schooling on Family Farms

I. Introduction

Since the early 1990s, the international community has been working toward the elimination of child labor, and substantial progress has been made. The total number of working children decreased by 11 percent between 2000 and 2006 (ILO, 2006). However, approximately 215 million children ages 5 to 17 years old, or 13.5 percent of this age group, were estimated to be engaged in child labor[15] in 2008 (ILO, 2008). The recent global financial and food crises have also increased the vulnerability of poor households and may underlie an increase in the incidence of child labor (Hong and Hou, 2011).

The cost of child labor is substantial. Working negatively impacts their performance at school, lowering their future earning capacity (Beegle et al., 2007). Children's working is not only the problem of the current generation, but it can lower the next generation's welfare due to the poverty that arises from the low educational attainment of working children (Basu and Tzannatos, 2003).

The leading cause of child labor is poverty, and child labor incidence can be reduced by alleviating poverty. Using a theoretical model, Basu and Van (1998) posited that children work for a household to survive at the subsistence level of consumption, and when adults' wages are high, children do not work. Empirical studies of child labor, however, show a mixed picture of the relationship between poverty and child labor. Since households' economic status can be

[15]Children engaged in child labor include "those in the worst forms of child labour and children in employment younger than 15 years old, excluding children older than 14 years in permissible light work" (ILO, 2010). This includes children working on family farms.

improved by child labor, the relationship is confounded by poverty-caused child labor and improved economic status through child labor. Ray (2000) found a strong negative relationship between income and child labor in Pakistan but did not find a significant relationship in Peru. Edmonds (2005) studied the role of economic growth on the reduction of child labor in Vietnam and found that 80 percent of the decline in child labor can be explained by an increase in per capita expenditures. Other studies, in contrast, have not found a negative relationship between household income and the child labor supply (Brown, Deardorff, and Stern, 2002). In relation to poverty-caused child labor, another important issue is how the child labor supply responds to child wages apart from other income since income from child labor is a part of household income. As the opportunity cost of not working (child wages) increases, children may work more (upward-sloping labor supply curve). If poverty is the main cause of child labor, however, as child wages decrease, children may need to work even more to compensate for the reduction in income (downward-sloping labor supply curve). Bhalotra (2000) found a downward sloping child labor supply curve in rural Pakistan and stronger results for boys than girls. A policy to reduce child labor should depend on the shape of child labor supply curve; for example, imposing a ban on child labor may reduce children's wages, which might increase poverty-caused child labor.

Poverty is, however, not the sole cause of child labor; the children of land-rich households work more than those of land-poor households (Bhalotra and Tzannatos, 2003), but the labor supply increases at a diminishing rate as land size increases (Basu et al, 2007). Bhalotra and Heady (2003) attributed this wealth paradox to labor and land market failures.

This study aims to determine the effect of child wages on the child labor supply on family farms and its relationship with household asset level. Since household farm child laborers are not paid wages, it is empirically difficult to estimate the effect of farm wages on the child labor supply on family farms. In this study, I first estimated the shadow wages for child farm workers using a farm production function and then investigated the effect of the estimated shadow wages on the child labor supply on family farms using an instrumental variable approach. In addition, this study investigates the effect of child shadow wages on the probability of school enrollment and schooling hours. If schooling and working are perfect substitutes, decreased working hours due to a change in the shadow wages of children would lead to increased school enrollment and schooling hours. However, if the rate of return to education is low, there is no strong incentive to attain education, so a decrease in child labor would not necessarily lead to an increase in educational attainment.

The structure of this paper is as follows: the theoretical framework is provided in section II; the data and empirical strategy for estimating child wages and the effect of those wages on the child labor supply are explained in section III; and the results and conclusion follow in sections IV and V.

II. Theoretical Framework

A household decides on the optimal level of children's education by maximizing the utility of the current household consumption plus the future value of children when they become either skilled or unskilled workers.

$$V = \log(c - \overline{c}) + \beta(ev_s + (T - e)v_u)$$

c : Household consumption

$\overline{c}$: Subsistence level of consumption

β : Parents' altruistic parameter for children

e : Current time spent on education

v_s : Child's future value as a skilled worker

v_u : Child's future value as an unskilled worker

T : Total time available

The functional form of utility for consumption is the log of consumption over the subsistence level ($\log(c - \overline{c})$). Parents discount a child's future value depending on their level of altruism (β). A child's future value is v_s if he/she becomes a skilled worker or v_u if he/she becomes an unskilled worker; for example, v_s can be treated as the wages of a skilled worker. The probability of becoming a skilled worker is a linear function of the time spent on education (e), and the probability of becoming an unskilled worker is a linear function of the total time available to children minus the time spent on education investment.

The household faces the following budget constraint:

$$c + pe \leq M + (T - e)w_C$$

p : Price of education

w_C : Child wages

M : Household income from sources other than child labor

$T = h + e$

It is assumed that children allocate their time to work (h) or schooling (e). The total household income consists of the income earned by children and other income (M). The total consumption plus the cost of education is smaller than the total household income.

From the first-order conditions, we can derive the optimal levels of consumption and children's education:

$$c^* = \frac{w_C + p}{\beta(v_s - v_u)} + \bar{c}$$

$$e^* = \frac{M + Tw_C - \bar{c}}{w_C + p} - \frac{1}{\beta(v_s - v_u)}.$$

The derivative of education with respect to child wages shows the effect of child wages on the child labor supply given that the optimal child labor supply (h^*) is negative with respect to the time spent on education (e^*).

$$\frac{\partial e^*}{\partial w_C} = \frac{p + \bar{c} - M}{(w_C + p)^2} \qquad \text{[Equation 1]}$$

The relationship between child wages and education (equation 1) depends on other income (M). If the other income does not cover the subsistence level of consumption and education cost ($p + \bar{c} > M$), then children spend more time on their education and less time working as child wages increase ($\frac{\partial e^*}{\partial w_C} > 0 <=> \frac{\partial h^*}{\partial w_C} < 0$). On the other hand, if the other income covers the cost of education and the subsistence level of consumption ($p + \bar{c} < M$), children spend less time on education and the child labor supply increases as child wages increase ($\frac{\partial e^*}{\partial w_C} < 0 <=> \frac{\partial h^*}{\partial w_C} > 0$).

e^* becomes zero (corner solution) when $\beta(v_s - v_u) < \frac{w_C + p}{(c - \bar{c})}$, meaning that the marginal benefit of education is smaller than the marginal cost of education. This corner solution is more likely to happen when the future value of a child ($\beta(v_s - v_u)$) is small, as when a parent is not altruistic or the difference in wages between skilled workers and non-skilled workers is small or when consumption exceeds subsistence-level consumption. In these cases, children will work regardless of the level of child wages.

This paper investigates how the child labor supply on family farms responds to child wages (the marginal productivity of child labor on family farms[16]) in accordance with the level of other income (M). When it comes to designing policy interventions for child labor, labor supply responses should be considered; if household income (M) cannot cover the subsistence level of consumption and education cost, increasing child wages will decrease the child labor supply. In

[16]We will discuss the marginal productivity of labor in section 3.B., "Empirical Strategy."

the case of household farms, increasing the marginal productivity of labor (the shadow wages of children labor) through better farm equipment or better land and water management will not only increase farm productivity or profit but also decrease the child labor supply. It is, however, an empirical question to determine whether the child labor supply increases with the rising marginal productivity of child labor after the household income passes a certain threshold point. This means that the same policy for non-poor household farms with child labor might result in the opposite consequences (i.e., increased child labor); therefore, for child labor on household farms above a certain household income level, policy focusing more on raising the returns of education ($v_s - v_u$) or developing the rural labor markets should be implemented. Policy interventions such as conditional cash transfer programs would be effective in reducing some poverty-caused child labor; however, it would not solve the problem of child labor among extremely poor families if the returns on education are too low and the opportunity cost of working is high.

III. Data and Empirical Strategy

1. Data

The Kagera Health and Development Survey (KHDS) is a longitudinal survey conducted by the World Bank. It includes 912 households surveyed annually from 1991 to 1994; ten years later, in 2004, 91 percent of them[17] were re-interviewed. This study uses the first four rounds (1991-94) of the KHDS. Kagera is located in northwestern Tanzania, covering four different agro-climatic zones (tree crop zone, riverine zone, annual crop zone, and urban zone; see the Appendix for detailed information). Between 1991 and 1994, 92 percent of the KHDS households had a

[17]At least one person from each household in 1991-1994 was traced and re-interviewed in 2004.

household farm.[18] While the KHDS is not a nationally representative sample from the Tanzanian population given the high proportion of households owning farms in Kagera, the KHDS is well-suited to studying the child labor supply on family farms.

The KHDS data includes a section on time use during the previous 7 days for all household members 7 years of age or older, separately for the employed, self-employed farmers, and self-employed business people. Based on this section, the hours worked on the family farm for children between 7 and 14 years old can be calculated, providing the dependent variable for the child labor supply model.

Among children between 7 and 14 years old, 63 percent of them had spent at least one hour working in the previous 7 days, excluding household work.[19] Most working children were engaged in work on the family farm; few of them worked as laborers or were self-employed (Table 1). On average, children working on the family farm had spent 10.7 hours working during the previous 7 days, and there was little difference in the number of working hours between children who worked on the family farm (unpaid family workers) and children who worked elsewhere (wage earners). There were, however, large differences in the number of working hours between the children who enrolled in school and those who did not: children with schooling worked far fewer hours than children without schooling. This correlation, however, does not imply that schooling leads to fewer working hours or vice versa.

[18]This means that at least one person in the household worked on the family farm. The number is based on the author's calculations.
[19]Household work includes collecting water and firewood, taking care of other family members, and cleaning.

Table 1. Percentage of working children and hours worked

	Percentage	Hours worked (past 7 days)		
	(%)	All	No School	School
Working on the family farm (1)	62.3	10.7	14.4	9.3
Working elsewhere (2)	0.6	11.2	17.0	6.7
Self-employed (3)	1.3	8.1	8.1	8.2
Working (1)+(2)+(3)	62.7	10.9	14.6	9.5
Doing household work	86.2	13.1	12.2	13.5

I used two sets of data in this paper: a household-level data set to estimate farm production to calculate the marginal productivity of child labor and a child-level data set to estimate the child labor supply and education. The sample for farm production only includes the 607 farm households with children working on the family farms,[20] and the final sample for the child labor supply includes all the children between 7 and 14 years old of those 607 farm households regardless of their working status.

2. Empirical Strategy

This study focuses on the child labor supply and educational responses to child wages (the opportunity cost of schooling) on the family farm. However, since a child working on the family farm does not usually work for wages, child wages are not explicitly measured. Jacoby (1993) estimated the opportunity cost of time for household workers to study the peasant family labor supply, and I will adopt his approach to study the child labor supply on family farms and its effect on child schooling. The basis of this approach is a two-stage maximization problem: first, a household makes a decision on the level of inputs, including labor input, by maximizing farm

[20] 899 households engaged in agriculture, including the production of agricultural goods for their own consumption. Since this paper focuses on the child labor supply on household farms, the sample excludes household without any children between 7 and 14 years old (702 households remained), and to estimate the shadow wages of children labor, the 607 farm households with children working were included.

profits, and then the household chooses the optimal level of consumption and education (or child labor) by maximizing utility (recursive method).

At the maximum level of farm profit, the marginal productivity of labor is equal to the shadow wages.

Max $\pi = F(L_A, L_C, K; A) - w_A L_A - w_C L_C - rK$

Farm production $F(.)$ is a function of adult labor (L_A), child labor (L_C), capital input (K), and total factor productivity (A). The input costs include the adult labor input cost ($w_A L_A$; w_A is the adult wage rate), child labor input cost ($w_C L_C$; w_C is the child wage rate), and capital input cost (rK). The optimal level of child labor input is set at $\frac{\partial F}{\partial L_C} = w_C$, meaning that the marginal productivity of child labor is the child (shadow) wages.

Empirically, the marginal productivity of child labor (MPL) can be estimated by estimating a farm production function. I estimated the MPL using two production functional forms: the Cobb-Douglas (CD) and Translog (TL) production functions. The CD production function does not allow the marginal productivity of one input to be dependent on the other input level (strong separability), while the TL production function is more flexible in that it allows the MPL of one input to be dependent on the level of another input [e.g., the marginal productivity of labor can be improved by better equipment (capital input)]. The regression equations for the CD function and the TL function are:

$$\ln Y_{ft} = a_0 + a_1 \ln L_{Cft} + a_2 \ln L_{Aft} + \delta' \ln K_{ft} + b' X_{ft} + u_f + e_{ft}$$

(Cobb-Douglas function)

$$\ln Y_{ft} = a_0 + a_1 \ln L_{Cft} + a_2 \ln L_{Aft} + \delta' \ln K_{ft} + \gamma_1 \ln L_{Cft} \ln K_{ft} + \gamma_2 \ln L_{Aft} \ln K_{ft} + b' X_{ft} + u_f + e_{ft}$$

(TransLog function)

Y_{ft} is the farm profit, L_{Cft} is the number of hours worked by children on the family farm, L_{Aft} is the number of hours worked by adults on the family farm, K_{ft} is a vector of capital inputs such as land, farm equipment, and livestock, and X_{ft} is a vector of household characteristics. Based on the estimation from the CD production function and the TL production function, the marginal productivity of child labor (shadow wages) is:

$$MPL_{ft} = \hat{a}_1 \frac{\hat{Y}_{ft}}{L_{Cft}} = \hat{w}_{Cft} \quad \text{(equation 2)}$$

$$MPL_{ft} = (\hat{a}_1 + \hat{\gamma}_1 \ln K_{ft}) \frac{\hat{Y}_{ft}}{L_{Cft}} = \hat{w}_{Cft} \quad \text{(equation 3)}$$

The parameters in this formula are estimated using ordinary least squares (OLS), random effects (RE), and fixed effects (FE) regression models. If there are unobserved characteristics correlated with both inputs and outputs at the household level such as managerial skills, an efficient family farm, or the coherence of farm household members ($Cov(X, u_f) \neq 0$), OLS estimates them and the random effects estimates are biased. Using a four-year longitudinal data set, I estimated the farm production functions using a fixed effect model, removing the potential bias from timeinvariant unobserved heterogeneity. In addition to the child shadow wages, the adult shadow wages ($\hat{w}_{Aft}$) are estimated in the same way.

The child labor supply and schooling are determined by the opportunity cost of schooling (shadow wages) and income excluding the child's earnings; we estimate following reduced-form model:

$$h_{it} = b_0 + b_1 \ln \hat{w}_{Cft} + b_2 \ln \hat{w}_{Aft} + b_3 Z'_{it} + e_{it} \quad \text{(second-stage regression)}$$

h_{it} is the number of hours worked on the family farm by an individual child, and Z'_{it} is a vector of the individual child and parents and household characteristics, including household assets. In addition to working hours (h_{it}), the number of hours spent in school and the probability of school enrollment are studied. As the shadow wage estimates are a function of the total number of hours worked by children on the family farm, an individual child's labor supply is endogenous to the shadow wage estimates; therefore, the ordinary least squares regression (OLS) will result in biased estimates.

I used an instrumental variable regression to identify the effect of child and adult wages on the child labor supply and education. The set of instrumental variables are the level of the current month's rainfall ($rain_t$) and the volatility of rainfall for the previous 6 months [$\text{var}(rain_{t,t-5})$] interacting with the ownership of water equipment on the farm [$rain_t * water_{ft}$ and $\text{var}(rain_{t,t-5}) * water_{ft}$], a variable indicating the presence of daily market in the town [$I(dailymkt_{rt})$], and the distance to the market if no daily market is present in the town [

$dist(mkt_{rt})$] interacting with the ownership of transportation equipment [$dist(mkt_{rt}) * trasp_{ft}$] for the child wage estimate and the adult wage estimate. Collecting water is one of the main tasks of children on farms, and the efficiency of child labor at a farm without water equipment will rely heavily on rainfall, and having water equipment moderates its reliance on rainfall (e.g., the negative effect of volatile rainfall on farm productivity may be dampened by having water equipment).

The first-stage regressions are as follows:

$$\ln \hat{w}_{Cft} = f(Z_{it}) + \theta_1 rain_t + \theta_2 \operatorname{var}(rain_{t,t-5}) + \theta_3 rain_t * water_{ft} + \theta_4 \operatorname{var}(rain_{t,t-5}) * water_{ft} + \theta_5 I(dailymkt_{rt}) + \theta_6 dist(mkt_{rt}) + \theta_7 dist(mkt_{rt}) * trasp_{ft} + v_{it}$$

(Child shadow wage)

$$\ln \hat{w}_{Aft} = f(Z_{it}) + \theta_1 rain_t + \theta_2 \operatorname{var}(rain_{t,t-5}) + \theta_3 rain_t * water_{ft} + \theta_4 \operatorname{var}(rain_{t,t-5}) * water_{ft} + \theta_5 I(dailymkt_{rt}) + \theta_6 dist(mkt_{rt}) + \theta_7 dist(mkt_{rt}) * trasp_{ft} + v_{it}$$

(Adult shadow wage)

The instrumental variable should be correlated with the shadow wages [$Corr(IV, \ln \hat{w}_{Cft}) \neq 0$], and correlated with the child labor supply only through the shadow wages [$Corr(IV, e_{it}) = 0$].

Finding the right instrumental variables that tease out child productivity from overall farm productivity can start with understanding the role of child labor on farms. It is widely known in the literature that the collecting water not only for drinking but also for farming is the role of children on farms. The following quote describes the importance of water equipment and how it relieves the work of children by increasing productivity ("Farm Implements for Small-scale Farmers in Tanzania" 1993).

> Finally, buckets (ndoo), tins (debe) (both 20 litres), and not least steel drums (pipa or dram) (200 litres) are very common household items. Metal buckets used for carrying water on the head are now possessed by most rural households and are increasingly supplied by indigenous rural and urban tin smiths because the twenty litre tins (debe) have become more difficult to obtain. Factory-made drums or barrels have become increasingly popular, both for beer making and not least for water storage and for ox-drawn water haulage by means of ox-carts or locally made sledges. Comprehensive ox-mechanization must involve a sufficient supply of steel drums greatly relieves women and children...

Furthermore, according to the data set, children under the age of 15 years spent a lot more time collecting water than any other family members. Knowing that fetching water is a job for children, it is reasonable to think that owning water equipment such as tins or water storage containers makes the work of children easy and efficient, but at the same time, it can directly affect the supply of child labor therefore it is endogenous to child labor supply. Nevertheless, if the region experiences a bad year in terms of rainfall because it was too volatile or dry, having water equipment would dampen the negative weather shock on productivity by assisting child labor productivity. Therefore, I use the variables that interact between water equipment ownership and the rainfall variables (both the level and volatility of rainfall for the previous 6 months). About 20 percent of children are from farm households with water equipment in our sample. In addition, adult shadow wages and household asset level are controlled for in the regression. Since the adult shadow wages may be endogenous to the child labor supply if child labor and adult labor are not separable, another set of instrumental variables are used.

Transactions involving final products or procurement of the input, which happens in the market, can be the job of adults rather than children, and the accessibility of the nearest periodic market affects the productivity of the farm. Therefore, I use the interaction between the presence of transportation equipment on farms (e.g. a bicycle or motorcycle) and the accessibility of the nearest periodic market – measured using the variable indicating that there is not a weekly market in the district and, if there is no weekly market, the distance to the nearest weekly market – along with the accessibility of the nearest periodic market. Both water equipment and transportation equipment, which can be endogenous to the child's labor supply are not a part of the instrumental variables and are excluded in the first-stage regression.

Finally, the estimation of the child labor supply in farm households with children working can be biased if there is a difference between households with working children and those without working children, conditional on having children in the household. To solve the potential selection bias, I calculated the inverse probability weight (IPW) of being in the selected sample, the sample of households with working children, using a probit model. With the estimated IPW, the child labor supply equation is re-estimated.

IV. Results

1. Farm Production and Shadow Wages

a) Descriptive Statistics: Farm Output and Inputs

Farm profit is the total output minus the input expenditures. The total output includes the value of the crops harvested – either sold or stored, the value of home processed products sold, the value of animal products, and the value of home-produced goods consumed by household members. All the units of the output and input values, including the total number of hours worked by children on the family farm are converted into monthly values,[21] and the monetary value of the outputs and inputs are reported in Tanzanian Shillings (TZS)[22] for survey years 1991-1994. Table 2 shows the descriptive statistics for the output and input values.

The average farm household produced 19,952 TZS and consumed 77 percent of their own products, which may indicate that the majority of farm households were engaged in subsistence farming. The input expenditures are very small relative to the total outputs, although the input expenditures for crop production, such as fertilizer or water, were not available. Fertilizer, however, was not widely used in Kagera during the survey period, and most of the crops produced in Kagera required low fertilizer use.[23] Also, in Kagera, there were few irrigated fields[24] and the farmers relied mostly on rainfall rather than on managed water. At the same time, the fixed effect model can deal with the potential bias due to the omitted input variables that do not vary over time in the farm production equation.

Regarding the farm inputs, on average, children worked 20 hours per week in total on the family farms, while adults worked 50 hours per week. The average area of cultivated land area was 5.4 hectares, 48 percent of households paid rent for the use of land, and the value of livestock was 6 times bigger than the value of farm equipment. The households had 2.3 children and 3.4 adults, on average, and 28 percent of households were headed by women. The heads of household had 4.1 years of schooling and were 50.4 years old, on average.

[21]In a 1991 survey, the units of farm outputs and inputs other than labor are one year; however, in the 1992-1994 surveys, the unit of these variables is 6 months. The labor input variable is generated based on the number of hours worked for the previous 7 days, and depending on the time of the interview, there is a mismatch between labor inputs and outputs. To correct this mismatch, I controlled for the interview months in the regressions.
[22]The exchange rate in 1991 was 196.6 TZS/1US$.
[23]See "Fertilizer Policy and Use in Tanzania" (IFPRI 2009).
[24]Only 14 percent of community leaders indicated having some irrigated fields in the village in the study sample.

Table 2. Average value of outputs and inputs

Variables	Mean	Std. dev.
Output-related variables (monthly, TZS)		
Total output (A+B+C+D)	19951.9	(21082.5)
Value of crops harvested (excl. consumed by hh) – A	17768.0	(54717.0)
Value of home-processed goods sold – B	5454.3	(16161.6)
Value of animal products – C	668.9	(7223.0)
Value of home-produced/consumed goods –D	15970.0	(16371.3)
Livestock input expenditures	173.4	(757.2)
Input expenditures for home production	102.1	(384.3)
Proportion of own products consumed (D/total output)	77%	26%
Profit (total output-input expenditures)	18299.0	(19719.6)
Input variables		
Hours worked (7~14 yrs old)/week	19.8	(19.7)
Hours worked (15+ yrs old)/week	50.2	(38.3)
# of HH member (7~14 yrs old)	2.3	(1.2)
# of HH member (15+ yrs old)	3.4	(1.8)
Size of land (hectare)	5.4	(4.7)
# of trees (crop tree)	3618.2	(11312.9)
Value of farm equipment	1193.5	(13209.0)
Value of livestock	7628.1	(15182.0)
Paying rent	48%	50%
Female HH head	28%	45%
HH head education	4.1	(3.2)
HH head age	50.4	(15.5)
Sample size (household-year)	1630	

Note: A, B, C, and D exclude the value consumed by HH members.

b) Marginal Productivity of Labor

Input elasticities on farm output are estimated using Cobb-Douglas (CD) and Trans Log (TL) production functions, and the results are shown in Table 3. As discussed in the empirical strategy section, the farm production function is estimated using both random effect (RE) and fixed effect (FE) models; the RE model assumes that a household's unobserved heterogeneity does not correlate with the controlled variables, while the FE model allows a household-specific error term to be correlated with covariates. To choose the appropriate model, I used the Hausman test to determine whether there is a systematic difference in results between the RE and the FE models.

Elasticity estimates from the CD production function are shown (Table 3). Based on the Hausman test, the hypothesis of no systematic difference is rejected with a Chi-square of 42.53 (p-value of 0.0387); in other words, there is unobserved household heterogeneity correlated with the farm inputs; thus, the elasticity estimates from the RE model are biased. The FE model, however, does not solve the issue of time-varying unobserved heterogeneity, although the short survey period (4 years) makes the existence of time-varying correlated errors unlikely. The elasticity estimates of child labor input (number of hours worked) do not vary over the models, while the elasticity estimate of adult labor from the FE model is half the size of the estimate from the RE model. This may imply that the unobserved household heterogeneity is correlated with the adult labor input on the farm but uncorrelated with the child labor input; the productivity of adult labor can be directly affected by the household's managerial skills or efficiency, while the productivity of child labor may not be a function of farm management skills or farm efficiency.

The input elasticity estimates from the Translog (TL) production function show that, overall, the productivity of each input does not depend on the level of the other inputs used, according to the FE model estimates. No interaction terms between two inputs (labor and size of the land, labor and value of farm equipment, and size of the land and value of farm equipment) are statistically significant. However, the inclusion of these interaction terms between two inputs weakens the significance of each input[25]; therefore, I used the elasticity estimates from the CD production function to calculate the marginal productivity of child labor. To control for the seasonality of input and output variables and the year-specific shock, the dummy variables of interview month and year are included in all the regression analyses.

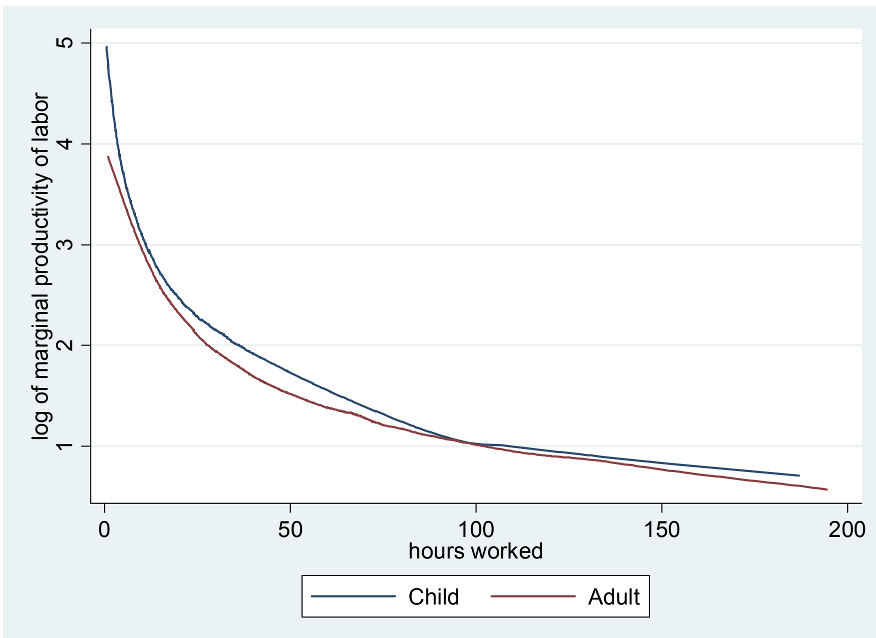
[25]This may be due to the little variation within the cell.

Table 3. Input elasticities (Cobb-Douglas)

	RE	FE
Cobb-Douglas		
log(Hours worked (7~14 yrs old))	0.076***	0.077**
	(0.028)	(0.033)
log(Hours worked (15+ yrs old))	0.141***	0.077*
	(0.035)	(0.046)
# of HH members (7~14 yrs old)	0.019	-0.026
	(0.025)	(0.040)
# of HH members (15+ yrs old)	0.061***	-0.027
	(0.016)	(0.033)
log(Size of land)	0.138***	0.115
	(0.053)	(0.077)
log(# of Trees (crop tree))	0.148***	0.109***
	(0.029)	(0.038)
log(Value of farm equipment)	0.017	0.027**
	(0.011)	(0.014)
log(Value of livestock)	0.006	0.012
	(0.007)	(0.013)
Paying rent	-0.055	-0.076
	(0.044)	(0.062)
HH head age	0.001	0.007
	(0.002)	(0.006)
Female HH head	0.093	-0.055
	(0.064)	(0.198)
HH head education (years of schooling)	0.023**	0.028
	(0.010)	(0.023)
HH head education (other form of education)	0.039	0.085
	(0.089)	(0.113)
HH farm self-employed	-0.059	-0.062
	(0.060)	(0.086)

Based on the elasticity estimate of child labor from the CD production function, the marginal productivity of child labor is calculated using equation 2. The mean of marginal productivity is 27.3 per hour for children and 8.6 per hour for adults; however, a much higher marginal productivity of child labor results from much fewer hours worked by children than by adults on family farms. The logs of the estimated marginal productivities of child labor and adult labor are plotted against their number of hours worked per week (Figure 1). This shows that there is little difference between the marginal productivity of labor for both children and adults. The estimated marginal productivity of labor (MPL) multiplied by the actual number of hours worked each week is, on average, 252.5 TZS for children and 253.7 TZS for adults, which may mean that children contribute to farm output as much as adults do and that child labor is an important source of household income.

Figure 1. Log of marginal productivity of labor for children and adults



2. Child Labor Supply and Education

According to the farm production function estimation, the marginal productivity of child labor input is estimated. The marginal productivity of child labor is the shadow wages of farm child laborers, and I use this estimate to study the effect of child shadow wages on the child labor supply. The shadow wages estimate is based on actual number of hours worked by children on a farm; however, I used instrumental variables to resolve the endogeniety problem. In the following sub-section, I will discuss the set of instrumental variables for the child shadow wages in more detail.

a) Instrumental Variables

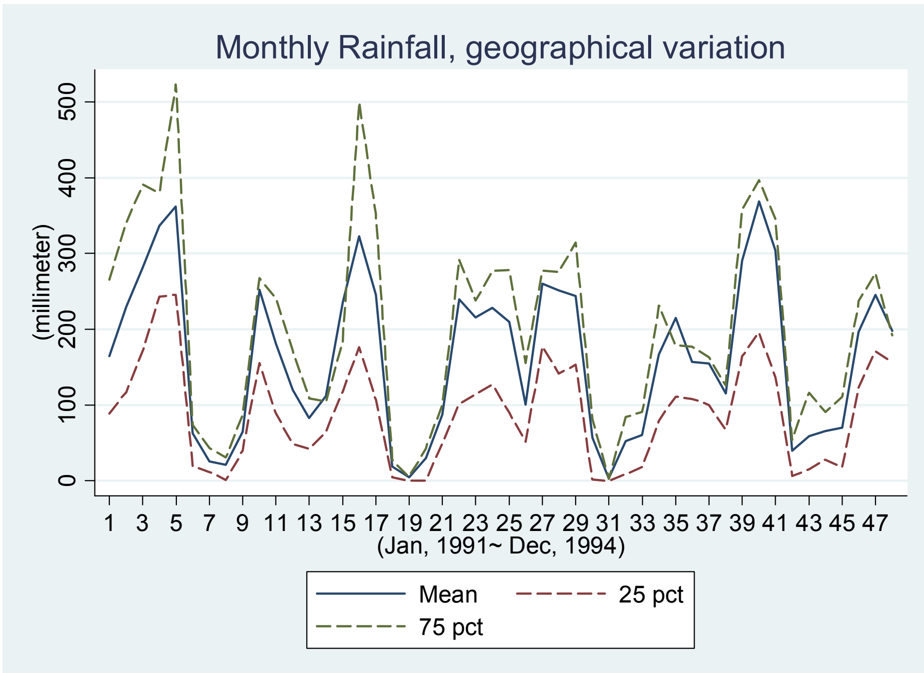
Farm productivity is affected by the availability of water, and farms in rural Tanzania during the survey years relied mostly on the rainfall of the region. The productivity of a farm, therefore, is affected by the level of rainfall in the current month and the volatility of rainfall for the past several months in the village. An excessive water supply hinders the crops' growth, and a constant stream of water leads to high yields[26] (FAO). Few irrigated fields are employed in Tanzania, and most farmers rely on the rainfall for their water supply. Rainfall can be extremely low in one month and high in another month, and the rainfall volatility of the past 6 months can vary by season, region, and year. The unpredictable volatile water supply (rainfall) can lower farm productivity while other farm inputs remain the same. There are dry and rainy seasons that farmers can predict, the effect of which will be captured by interview month dummies; however, there is also unpredictable volatility in the rainfall. The rainfall data is from the Tanzania Meteorological Agency and includes the rainfall level (in millimeters) from 21 weather stations in Kagera during the survey period. The villages in the KHDS are matched to the nearest and the second-nearest weather station. If the rainfall information from the nearest weather station is not available in a certain month, information from the second-nearest weather station is used.

Figure 2 shows the monthly rainfall pattern and geographical variations. I report the mean, 25th percentile, and 75th percentile of the geographical rainfall distribution within each month. In

[26]http://www.fao.org/landandwater/aglw/cropwater

general, during the rainy season,[27] the geographical variation is greater than during the dry season; thus, the volatility of the rainfall varies across interview months, years, and regions. Depending on the agronomic zone,[28] the crops that farmers grow and their relationship with the rainfall differ, so I included dummies for each agronomic zone in the regression.

Figure 2. Monthly rainfall over time and its geographical variation



As discussed in the methodology section, the level and volatility of rainfall over the past 6 months and its interactions with ownership of water equipment and local market accessibility are used as instrumental variables for the shadow wages of children and adults. The market accessibility is measured by the presence of a weekly market in the village and the distance (km) to the nearest weekly market if there is no market in the village. These instruments are included in the first-stage regression, and the results are shown in Table 4. A 100mm increase in rainfall

[27]Tanzania has two rainy seasons, from October to December and from March to May.
[28]See the Appendix for detailed information about the zones.

results in a 12.6 percent increase in the shadow wages of children but does not affect the shadow wages of adults significantly. Furthermore, the volatility of rainfall decreases the shadow wages of children but does not have an impact on the shadow wages of adults. Ownership of water equipment, however, reverses the impact of rainfall, meaning that the ownership of water equipment dampens the impact of rainfall shock on farm productivity. This may be explained by the role of child labor on the farm. Since fetching water is children's work on the farm, the rainfall shifts the marginal productivity of children but not the marginal productivity of adults. The absence of a weekly market in the village decreases the shadow wages of both children and adults, and the negative effect is larger for adults. The distance to the nearest weekly market does not have a significant impact on the shadow wages; however, its interaction with ownership of transport equipment results in increased shadow wages for children. The F statistics for the excluded variables is 10.9 for child shadow wages and 4.76 for adult shadow wages, and the F statistics for the instrumental variables are 29.05 and 20.02 for the child and adult shadow wages, respectively.

Table 4. First-stage regression

	Log(shadow wages, child)	Log(shadow wages, adult)
Mean(Rainfall), over past 6 months	0.126**	0.044
	(0.015)	(104)
Std(Rainfall), over past 6 months	-0.251***	-0.004
	(0.062)	(0.057)
Water equip*Mean rainfall	-0.340***	-1.902
	(0.135)	(0.124)
Water equip*Std rainfall	0.600***	-0.021
	(0.156)	(0.144)
No weekly market in town	-0.259***	-0.280***
	(0.066)	(0.061)
Distance to nearest weekly market	0.005	0.003
	(0.005)	(0.004)
Distance to nearest weekly market*Transport	0.032***	0.009
	(0.007)	(0.006)
F(7, 1502)	10.9	4.76
F(42, 1502)	29.05	20.02

b) Impact of Shadow Wages (Marginal Productivity of Labor) on the Child Labor Supply and Education

The regression results from OLS are shown in Table 5. The first column shows the association between the shadow wages of child labor and the labor supply. The child labor supply is apparently negatively correlated with the shadow wages of children since the marginal productivity of labor decreases as the labor supply increases; this negative coefficient indicates the reverse causality rather than the response of the child labor supply to a change in the shadow wages. Age is an important factor in the child labor supply, along with gender. Older children work more and boys work more than girls. Ownership of water equipment is positively related with the child labor supply, and the shadow wages of adults and household assets are not significantly associated with the child labor supply. The probability of school enrollment and number of hours spent in school are positively related with the shadow wages of children. A 100 percent increase in the shadow wages of children is correlated with an increase in the probability of school enrollment by 2.5 percent and 1.6 schooling hours. This, however, may also result from the higher marginal productivity of labor for the children who work less and, in turn, may be more likely to be enrolled in school and spend more time in school (second and third columns in Table 5). Assets, unlike the child labor supply, are positively related with schooling hours.

Table 5. Child labor supply and education: OLS

	Hours worked	School enrollment	Hours spent in school
Log(shadow wages, child)	-5.824***	0.025*	1.610***
	(0.320)	(0.014)	(0.437)
Log(shadow wages, adult)	-0.435	-0.008	-0.678
	(0.296)	(0.015)	(0.519)
Age	0.881***	0.085***	2.794***
	(0.096)	(0.006)	(0.171)
Girl	-1.959***	-0.011	-0.054
	(0.482)	(0.029)	(0.842)
Ownership of transportation	0.260	0.088***	2.889***
	(0.531)	(0.032)	(0.956)
Ownership of water equipment	2.623***	-0.010	-0.892
	(0.951)	(0.040)	(1.365)
Assets – 3rd quintile	0.563	0.071	4.315***
	(0.833)	(0.047)	(1.395)
Assets – 4th quintile	1.207	0.076	1.425
	(0.870)	(0.049)	(1.469)
Assets – 5th quintile	1.451	0.102*	3.478**
	(0.988)	(0.053)	(1.632)

Note: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level. Other covariates included in the regression but not shown are dummies for a child's sickness and being orphaned, years of education (mother and father), age of parents, number of household members between 7 and 14 years old, number of household members 15 years old or older, size of the land, size of the land squared, dummies for interview month and year, and 5 agronomic zone dummies.

An instrumental variable (IV) regression approach is employed to solve the reverse causality issue, and the results from the IV regression using the generalized method of moments (GMM) are shown in Table 6. A 100% increase in the shadow wages of children (MPL) results in a reduction of the child labor supply by 5.9 hours per week, while there is no significant effect of adult shadow wages on the child labor supply. The results contradict the conventional upward sloping labor supply curve; however, the negative coefficient of child shadow wages confirms that, as shown in the theoretical framework, a child needs to work more as wages decrease since child labor is necessary for a household's survival when household income is not enough to cover the subsistence level of consumption, including schooling cost.[29] This means that, by working on the farm, children support themselves to meet the subsistence level of consumption and schooling cost. Age and gender are still significant factors for the child labor supply, and ownership of transportation and water equipment do not have a significant impact on the supply of labor, and neither do assets. In terms of the probability of school enrollment, the shadow wages of both children and adults do not matter, while having more assets increases the probability of school enrollment. However, the number of hours spent in school increases significantly as child shadow wages increase – 5.6 hours per week in accordance with a 100% increase in the shadow wages of children. This shows that the school enrollment decision itself may not be influenced by children's working since children can both work and attend school at the same time; rather, the children may sacrifice their schooling hours for work.

In sum, the results show that a decrease in child labor productivity results in more working hours and fewer schooling hours but does not affect the school enrollment rate. This may, therefore, imply that targeting school enrollment to reduce child labor may not be a good policy option; rather, efforts to increase the farm productivity of child labor lead to fewer working hours and more schooling hours.

[29]It also confirms the theory that child labor is caused by poverty where the substitution effect dominates the income effects under the subsistence level of consumption (Bhalotra, 2003).

Table 6. Child labor supply and education: IV regression (GMM estimation)

	Hours worked	School enrollment	Hours spent in school
Log(MPL, child)	-5.893***	0.052	5.557***
	(1.078)	(0.060)	(2.056)
Log(MPL, adult)	2.040	-0.044	-4.683
	(1.950)	(0.094)	(3.187)
Age	0.821***	0.085***	2.926***
	(0.106)	(0.006)	(0.191)
Girl	-1.945***	-0.012	-0.134
	(0.492)	(0.029)	(0.904)
Asset – 3rd quintile	0.142	0.067	4.015***
	(0.912)	(0.049)	(1.537)
Asset – 4th quintile	0.963	0.083*	1.283
	(0.892)	(0.050)	(1.543)
Asset – 5th quintile	0.974	0.111**	3.521*
	(1.066)	(0.056)	(1.833)

Note: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level. Other covariates included in the regression but not shown are dummies for a child's sickness and being orphaned, years of education (mother and father), age of parents, number of household members between 7 and 14 years old, number of household members 15 years old or older, size of the land, size of the land squared, dummies for interview month and year, and 5 agronomic zone dummies.

Since gender is an important determinant of the child labor supply, the effect of child wages on the labor supply may differ by the gender of the child. Table 7 shows the gender difference in the semi-elasticity of child shadow wages on the labor supply. Boys' labor supply is much more elastic than girls' labor supply. For boys, doubling the shadow wages leads to a reduction in the number of working hours by 8.5 hours per week, but for girls, it reduces the number of working hours by 2.4 hours per week. These results can be explained by the gender-specific division of labor. Girls specialize in home production and boys specialize in farm production[30]; hence, productivity shocks on the farm would not affect girls' labor supply on farms as much as boys'. School enrollment, again, is not affected by changes in the shadow wages for either boys or girls. Schooling hours, however, are affected by child shadow wages almost equally for both genders. A 100% increase in the shadow wages leads to an increase of 6.7 schooling hours for boys and

[30]Girls spent 13 hours per week on household work, on average, and boys spent 9.6 hours per week.

5.4 schooling hours for girls. The wages of adults do not affect the child labor supply for either boys or girls.

Table 7. Child labor supply and education: IV regression (GMM estimation), by gender

	Boys			Girls		
	Hours worked	School enrollment	Schooling hours	Hours worked	School enrollment	Schooling hours
Log(shadow wages, child)	-8.496***	0.078	6.655**	-2.423**	0.049	5.371**
	(1.852)	(0.086)	(3.355)	(1.051)	(0.075)	(2.414)
Log(shadow wages, adult)	-0.605	-0.041	-8.547*	2.846	-0.058	-2.286
	(2.794)	(0.137)	(4.787)	(2.331)	(0.121)	(4.033)
Age	0.764***	0.099***	3.111***	0.968***	0.074***	2.725***
	(0.152)	(0.008)	(0.280)	(0.131)	(0.009)	(0.256)
Asset – 3rd quintile	0.845	0.006	4.397*	0.211	0.117*	3.935*
	(1.483)	(0.066)	(2.390)	(1.252)	(0.071)	(2.137)
Asset – 4th quintile	2.161	0.062	2.042	-0.071	0.119	-0.164
	(1.364)	(0.064)	(2.202)	(1.215)	(0.073)	(2.238)
Asset – 5th quintile	2.338	0.077	4.247*	-0.632	0.155*	2.342
	(1.483)	(0.069)	(2.469)	(1.765)	(0.090)	(2.945)

Note: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level. Other covariates included in the regression but not shown are dummies for a child's sickness and being orphaned, years of education (mother and father), age of parents, number of household members between 7 and 14 years old, number of household members 15 years old or older, size of the land, size of the land squared, dummies for interview month and year, and 5 agronomic zone dummies.

If poverty is the cause of child labor, then the elasticity on labor supply may depend on household income. For lower-income households, the child labor supply can be downward sloping, while for rich households, the child labor supply can reflect the traditional upward slope. Here, I test to determine whether the child labor supply and schooling differs by household asset level since household income is also endogenous to the child labor supply. One thing to keep in mind is that the sample region is rural Tanzania, where most of the population lives in poverty; therefore, having a high level of assets[31] does not mean that they are rich, but they are relatively better off than other households in that region, and at the same time, the analysis sample for the child labor supply includes only farm households with children working. The set of regression results by asset level is shown in Table 8. With a 100 percent increase in the shadow wages, the child labor supply decreases by 6.4 hours for the low-middle asset level households and 4.7 hours for the households with high asset levels. This shows that the relatively richer households have a less elastic child labor supply compared to the poorer households; however, it still presents the downward labor supply regardless of asset level in rural Tanzania. Given that the households with high levels of assets in the sample have US$156 per capita expenditures (yearly), the negative semi-elasticity of the child labor supply is not surprising.

Table 8. Child labor supply and education: IV regression (GMM estimation), by asset level

	Low-middle asset level			High asset level		
	Hours worked, past 7 days	School enrollment	Schooling hours, past week	Hours worked, past 7 days	School enrollment	Schooling hours, past week
Log(MPL, child)	-6.387***	0.058	5.329**	-4.672***	-0.077	0.710
	(1.457)	(0.072)	(2.382)	(1.428)	(0.072)	(2.714)
Log(MPL, adult)	3.181	0.037	-6.314	0.443	-0.063	-2.537
	(3.240)	(0.178)	(5.874)	(1.928)	(0.083)	(2.766)
Age	0.868***	0.082***	2.858***	0.866***	0.085***	2.932***
	(0.149)	(0.008)	(0.245)	(0.140)	(0.008)	(0.248)
Girl	-1.495***	-0.039	-0.273	-2.734***	0.055	1.429
	(0.557)	(0.036)	(1.055)	(0.759)	(0.041)	(1.359)

Note: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level. Other covariates included in the regression but not shown are dummies for a child's sickness and being orphaned, years of education (mother and father), age of parents, number of household members between 7 and 14 years old, number of household members 15 years old or older, size of the land, size of the land squared, dummies for interview month and year, and 5 agronomic zone dummies.

[31]The median per capita yearly expenditures are 21,308 TZS (108 USD with an exchange rate of TZS 196.6/USD1) for households with low-middle asset levels and 30,746 TZS (156 USD) for households with high asset levels.

3. Correcting the Sample Selection

Since the shadow wages of the children in households without working children were not estimated, the previous regression results of the child labor supply are valid only for the households with children working. The difference between the selected sample (households with child labor) and that of the whole sample are reported in the Appendix. Overall, there is little difference between the two samples, but one notable difference is that the adults in the selected sample, on average, work more hours than the whole sample average, while the average household size is similar in both samples. To correct the potential sample selection bias, I calculated the inverse probability weight (IPS) by estimating the probability of being in the selected sample as a function of observable characteristics. This method is widely used to correct the non-random missing bias in the survey responses (Wooldridge 2002).

$$\Pr(s_{ht} = 1 \mid x_{ht}) = \frac{\exp(x_{ht}\beta)}{1 + \exp(x_{ht}\beta)}$$

Using logistic regression, I calculated the probability of being in the sample, and the inverse of this probability is used to reweight the selected sample.

With the corrected weight, there is little change in the coefficient estimates, and the overall findings of this study indicate that the child labor supply curve is downward-sloping for the low-middle asset level, and this negative wage effect weakens but is still significant for the high-asset level households (Table 9).

Table 9. Child labor supply: sample correction

	Low-middle asset level	High asset level
Log(MPL, child)	-6.252***	-4.139***
	(1.340)	(1.477)
Log(MPL, adult)	2.986	-0.948
	(3.254)	(1.984)
Age	0.773***	0.863***
	(0.159)	(0.143)
Girl	-1.551***	-2.653***
	(0.575)	(0.760)
Ownership of transportation	-0.398	-0.313
	(0.662)	(1.109)
Ownership of water equipment	-0.240	1.385
	(1.931)	(1.042)

Note: * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level. Other covariates included in the regression but not shown are dummies for a child's sickness and being orphaned, years of education (mother and father), age of parents, number of household members between 7 and 14 years old, number of household members 15 years old or older, size of the land, size of the land squared, dummies for interview month and year, and 5 agronomic zone dummies.

V. Conclusion and Discussion

This study addresses how the child labor supply and educational investment respond to changes in wages. In the theoretical framework, it is shown that child labor decreases as child wages increase when household income does not cover the subsistence level of consumption and educational cost. This is opposite to the upward-sloping labor supply curve, which reflects the fact that the labor supply increases as wages increase when the income effect dominates the substitution effect. The empirical results confirm this downward-sloping labor supply curve in rural Tanzania, where most of the population lives in poverty. It is estimated that there would be a reduction of 5.8 hours in child working hours per week in response to a 100% increase in child shadow wages. In terms of the educational response to the opportunity cost of schooling (shadow wages), the probability of school enrollment does not decrease or increase in response to the child shadow wages; however, the schooling hours increase by 5.6 hours per week as child shadow wages increase by 100%. This indicates that schooling and working are substitutes, although a child can be enrolled in school while working at the same time. This study also finds that boys' labor supply is much more elastic than girls' labor supply, which can be explained by the gender-specific division of labor. Girls specialize in home production and boys specialize in farm production.

Time spent in school can be increased as child wages increase through a reduction in working hours since the time spent in school and working hours are substitutes. Nevertheless, as shown in the theoretical framework, the corner solution (educational investment is zero) occurs when the returns of education are smaller than the marginal cost of schooling. The school enrollment rate will not increase even if poverty is reduced through an increase in farm productivity if the expected returns of education are too low. It is empirically estimated that attending school is not related to the shadow wages of children in rural Tanzania, where there are few job opportunities and the quality of schools is bad; hence, it is likely that the returns of education are low.

In rural areas, the labor market is underdeveloped and a child labor ban is not a practical policy option even aside from the unintended consequences of such a ban. Reducing poverty by increasing farm productivity results in a decrease in child labor incidence even though the opportunity cost of schooling increases. In turn, children may spend more time in school; however, their educational attainment, in the end, may not be affected much by poverty reduction or an increase in income. Rather, a policy that targets the improvement of school quality and local employment opportunities may result in an increase in educational attainment through an increase in returns on education.

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Appendix

Agronomics Zones in Kagera

• Tree Crop Zone: Low fertility soils in areas of high rainfall, where the main crops are bananas, coffee, and tea. This zone is in the northern part of Kagera with communities in Bukoba Rural and Muleba Districts.

• Riverine Zone: Alluvial and colluvial soils of considerable potential, but requiring flood control, where the cropping pattern is mixed and includes cereals, sugarcane, rice, and legumes, as well as tree crops. This zone is in the middle of the region; most of its communities are in Karagwe and Bukoba Rural Districts and a few in Muleba District.

• Annual Crop Zone: Soils of low to medium fertility with moderate potential and lower rainfall, where the cropping pattern is mixed and includes groundnuts, cassava, beans, cotton as well as some cereals (maize, sorghum) and pasture, but few tree crops. This is in the southern part of Kagera in Biharamulo and Ngara Districts.

• Urban Zone: The town of Bukoba, the region's capital, plus an additional 27 communities in Muleba, Karagwe, Ngara, and Biharamulo Districts that were designated as urban by the 1988 census.

Appendix Table. Sample Description

	Analysis Sample		Whole Sample	
	Mean	Std.	Mean	Std.
Output related variables				
Total Output (A+B+C+D)	19951.9	(21082.5)	18958.9	(19970.0)
Value of crops harvested - A	17768.0	(54717.0)	16419.7	(48080.5)
Value of home processed goods - B	5454.3	(16161.6)	4924.9	(14999.5)
Value of animal products - C	668.9	(7223.0)	563.4	(6604.6)
Value of home produced/consumed goods -D	15970.0	(16371.3)	15307.6	(15948.9)
Livestock input expenditure	173.4	(757.2)	145.9	(668.6)
Input expenditure for home production	102.1	(384.3)	94.6	(355.5)
Proportion of own consumption (D/Total Output)	77%	26%	78%	26%
Profit (Total Output-input expenditures)	18299.0	(19719.6)	17515.7	(18766.7)
Input Variables				
Hours worked (7~14 yrs old)	19.8	(19.7)	14.5	(18.9)
Hours worked (15+ yrs old)	50.2	(38.3)	44.3	(37.9)
# of HH member (7~14 yrs old)	2.3	(1.2)	2.2	(1.2)
# of HH member (15+ yrs old)	3.4	(1.8)	3.3	(1.8)
Size of Land	5.4	(4.7)	5.1	(5.4)
# of Trees (crop tree)	3618.2	(11312.9)	3310.0	(10028.4)
Value of farm equipment	1193.5	(13209.0)	1063.2	(11703.7)
Value of live stock	7628.1	(15182.0)	6700.8	(14214.5)
Paying Rent	48%	50%	48%	50%
Female HH head	28%	45%	28%	45%
HH head Education	4.1	(3.2)	4.1	(3.3)
HH head age	50.4	(15.5)	49.9	(15.7)
HH farm self employed				
Sample Size (Household-year)	1630		2286	

Chapter 3. Long-term Impact of Free Tuition and Female Stipend Program on Educational Attainment, Age of Marriage, and Labor Force Participation of Married Women in Bangladesh[32]

I. Introduction

In many developing countries, household's investments in children's education have been historically often made in favor of boys, especially when economic resources are limited. Although significant progress has been made toward gender equality in education, there is still pronounced gender disparity, particularly, at the secondary and higher levels of education. These gender disparities appear to be more acute in South Asia and North and West Africa regions (World Development Report, Gender, 2012). Furthermore, the gender gap is exacerbated among the poorest households who are faced with the drastic choice of sending one child or none to school (Filmer, 2008). In South Asia in particular, cultural norms and economic factors collude to prevent girls from attending school. Furthermore, women's mobility and social interactions are often bounded inside the household, making it difficult for most girls to achieve higher levels of education (Glick, 2008).

The labor market in South Asia is also generally marked by wage discrimination and fewer employment opportunities for women, leading to lower returns to schooling for girls compared to boys, which, in turn, induce lower investments in girls' education (Das and Desal, 2003). Economic literatures have shown some evidence that, with increasing employment or economic opportunities for women, investment in girls' education can also rise (Qian, 2005; Munshi and Rosenzweig, 2004; and Jensen, 2012, and Heath and Mobarak, 2012).

[32] This chapter is co-authored with Leopold Remi Sarr at World Bank.

In light of this multidimensional problem, narrowing the gender gap in education has become a primary goal for the international development community (UN Millennium Development Goal). In response, policies promoting girls' education, either through demand side (e.g. stipend to girls) or supply side (e.g., more girls' school), have been implemented across the developing world. Examples of such demand side interventions are the free tuition policy for secondary school girls and the Bangladesh Female Secondary School Assistance Program (FSSAP), which is the first conditional cash transfer (CCT) program implemented in the developing countries. A handful of studies describe the upward trend in girl's secondary school enrollment rate and contribute it to the FSSAP. There is also evidence that FSSAP did not only narrow, but it also reversed the gender gap in secondary school enrollment (Fuwa, 2001; Asadullah and Chaudhury, 2009; Patrinos, 2008)[33]. The success story of the Bangladesh female stipend program has caught the attention of the international development community and induced number of countries to adopt similar approaches (Khandker et al, 2003; Arends-Kuenning and Amin, 2004; Raynor and Wesson, 2006; Schurmann, 2009). However, prior to the FSSAP, the Bangladesh government had introduced another major gender-targeted education policy. Such program offer free tuition to female students enrolled in grade 6 to 8 in 1990, and ignoring this policy could lead to bias estimation of the impact of FSSAP. In addition to narrowing the gender gap in education, the FSSAP purposed to delay marriage by providing stipend to girls as long as they remained unmarried. Early marriage is associated with adverse health outcome for the mother and the child, higher fertility rate and experiences in domestic violence (Raj et al, 2010; Jensen and Thornton, 2003). Early marriage in Bangladesh is a widespread social phenomenon; in 2000, 50 percent of women were married by the time they reached 15 years old (Demographic and Health Survey 1999/2000).

[33] Boys' schooling would have been displaced by girls' schooling if households needed additional labor to help with household's work which had been traditionally girls' work.

Besides achieving gender equality in education, the goal of educating girls is to increase female labor force participation, which, in turn, contributes to the country's economic growth. A large body of literature focusing on the returns to education around the world sees the benefit of education through the lens of economic returns (Angrist, 1995; Card, 1999; Duflo, 2001). While the benefit of education is universally recognized, studies have shown that the returns to education in developing countries are higher than those in developed countries (Pscharopoulos, 1994). Economic returns to education, however, become questionable when there is limited employment opportunity for women, which could be due to social and/or economic barriers. In South Asia, female labor force participation is the second lowest, 35 percent in the world, after Middle East and Northern Africa, 26 percent. On the other hand, men's labor force participation is almost universal (World Development Report, Gender, 2012). Furthermore, the relationship between education and women's labor market participation is shown to be non-linear. In India, U-shaped relationship is found where education is negatively associated with labor force participation for women with lower end of education spectrum. However, the relationship is reversed for women with higher than middle school education, which would potentially explain the observed higher returns to education for highly educated women (Kindong and Unni, 2001, Das and Desal, 2003). Therefore, there is heterogeneity in returns to girls' education, and it is an empirical question as to what extent the gender targeted education policies could translate into actual increase in female labor force participation.

Given this background, this study first evaluates the primary impacts of two policies: impacts of free tuition policy in 1990 and female secondary school assistance program in 1994 on women's educational attainment and age of marriage. Then, we focus on estimating the impact of education on labor market participation of women who were affected by the free tuition policy and the FSSAP. We find that FSSAP has led to a significant positive impact on the number of years of education of women and to a delay in the age of marriage while the free tuition policy did not lead to any significant impact on their educational attainment. The impact of education on female labor force participation is sensitive to sample selection and the stipend program raised the labor force participation by about 9 percent for women with at least five years of education.

We provide a background of the female secondary education policies in Bangladesh in section 2; describe the identification strategy in section 3; examine the trend of educational attainment, age of marriage, and labor force participation for women and men in Bangladesh in section 4; estimate the program impacts on set of outcomes in Section 5; and lastly discuss the policy implications of our findings before providing some concluding remarks in section 5.

II. Background – Free Tuition Policy and Female Secondary School Assistance Project (FSSAP) in Bangladesh

In order to raise the female educational attainment and thereby increase women's economic participation and social status, the Government of Bangladesh (GOB) introduced the free tuition policy for female students of grade 6 to 8 in 1990. Four years after the implementation of the free tuition policy, in 1994, the World Bank and the GOB jointly initiated the Female Secondary School Assistance Program (FSSAP) and the free tuition policy was carried by the FSSAP through tuition subsidy to the school in which the participating FSSAP students were enrolled. Both policies were implemented in rural areas nationwide[34].

While the FSSAP has several components, the primary component was the Female Secondary School Stipend Program (FSSP), which provides monthly stipends to female students from Grade

[34] All 460 rural upazilas in the country.

6 to Grade 10, that is, students 11 to 15 years old[35]. Stipends were provided as long as the students meet the following conditions: i) maintain at least 75% attendance, ii) secure at least 45% marks in the annual examinations, and iii) remain unmarried. A detailed description of FSSAP is shown in Table 1. The stipend covered a portion of direct costs of schooling and was given directly to female students who withdraw the cash from their personal bank account. Annual direct cost of secondary education per student was about US$ 54 in 1998. This includes tuition and other direct costs such as uniform, textbooks, and examination fee, and 42 percent of the direct educational cost was spent on tuition. US$ equivalent of the total annual stipend for a girl ranges US$12 for grade 6 to 30.25 for grade 10. Besides the stipend, tuition subsidy was provided to the school in which the eligible female students enrolled (Liang, 1994).

Table 1. Stipend and Tuition Rate in Taka

Grade in 1994	Monthly Stipend	Book Allowance	Monthly Tuition Subsidy to school	Exam Fee	Starting year
6	25	15	10		Jan, 94
7	30	15	12		Jan, 95
8	35	15	12		Jan, 96
9	60	20	15	250	Jan, 94
10	60	20	15	250	Jan, 95

Source: World Bank Project Performance Assessment Report, 2003 (Credit 2469).

The FSSAP program has been credited with narrowing the gender gap in secondary school enrollment (Schurmann, 2009). According to the Household Income and Expenditure Survey (HIES), the gross enrollment rate for girls aged 11-15 has increased from 43.7 percent in 1995 to 60.4 percent in 2005 whereas, that for boys has only gone up from 47.9 percent to 52.2 percent

[35] The following components of the project were implemented: (i) the stipend program provided to the female secondary school students, (ii) extensive information campaign to raise public awareness on the importance of female education and the ensuing social and financial benefits, (iii) enhancing the school infrastructure, recruiting female teachers and providing occupational training to girls leaving school, and (iv) encouraging community participation through parent-teacher associations. However, the implementation of the latter three components (ii-iv) was limited due to the budget shortage and the expansion of the stipend program (World Bank Project Performance Assessment Report, 2003).

over the same period. Fuwa (2001) provides evidence that FSSAP resulted in a decline in boy's enrollment rate; hence the program was able to narrow the gender gap in education by not only increasing enrollment rate for girls but also lowering enrollment rate for boys. However, there is some evidence presenting increasing trend in female enrollment before the implementation of FSSAP in 1994. For example, according to the Bangladesh Educational Statistics, the share of girls enrolled in junior secondary school (grade 6 to 8) grew from 35 % in 1990 to 51 % in 1994, and again to 58 % in 2005. The narrowing of the gender disparity in secondary schooling was also prevalent before 1994; between 1983 and 1993, girl's secondary school enrollment rate increased by 9.4 percent annually while boy's enrollment rate increased only by 3.4 percent (World Bank Project Performance Assessment Report). This could be attributed to the free tuition policy introduced in 1990.

Although a great deal of attention has been devoted to the success of FSSAP in narrowing the gender disparity in secondary school enrollment, to date, there exists no rigorous study which attempts to separate the impact of the free tuition policy from that of the FSSAP on educational attainment nor is there any study that looks at the impact of both policies on the age of marriage and on female labor market participation. Furthermore, taking into account the potential spillover effects of FFSAP on boys' schooling, comparing the enrollment or educational attainment of men and women would not be the best strategy that most of existing literatures on the impact of FSSAP on female education employ. In contrast, this study uses an identification strategy that exploits geographical variation in FSSAP coverage.

This paper aims to answer three questions; i) what are the impacts of these two policies on women's educational attainment?; ii) what impacts do they have on their age of marriage?; and iii) what are their impacts on the labor force participation of married women? We use the Demographic and Health Surveys (DHS, 2007) to investigate these questions. Since DHS includes only married women, we focus our analysis on the impacts of these policies for married women. Although the estimates of this study are applicable to only married women, the external validity of our estimates is quite robust, given that the majority of women marry by early 20s. In fact, 84 percent of 23 years old women are married and 93 percent of women age 23 to 34 are married, according to the 2010 HIES. However, it should be noted the potential bias arising from the married women sample if more educated women or working women marry late. Under these conditions, the impacts would be underestimated.

III. Trend in Educational Attainment, Age of Marriage, and Labor Force Participation

We first present descriptive statistics on the years of education and the age of marriage across age cohorts and by rural and urban categories. Here, rural and urban are categorized based on the hometown of respondents not based on the current residence. Because both the free tuition and the FSSAP have been implemented in rural areas, we would expect the years of education for the eligible rural age cohorts increase more than that for their urban counter part. Women born in 1976 and lived in rural areas are the oldest cohort eligible for the free tuition whereas women who were born in 1979 and lived in rural areas are the oldest cohort eligible for the FSSAP. As we can see in Figure 1, the average number of years of education of women who were born in 1976 or later and lived in urban areas (post control group) has been declining for the younger cohort while women who were born in 1976 or later but lived in rural areas (post treatment group) exhibit an upward trend in years of education. In the meantime, for both urban and rural cohorts, the average number of years of education of the age cohorts born before 1976 (pre control and treatment groups) had been increasing. Similarly, a graph is shown for the age of marriage, in Figure 1. Before we draw any implication from this graph, caution should be made because the sample is restricted to married women or men. We would then expect to see the age of marriage declines as the cohort becomes younger, even if the trend is in fact going in the opposite direction. The age of marriage, for the post control group, has declined while the age of marriage, for the post treatment group has, overall, remained constant except for the far right tale of age distribution (age between 18 and 20).

We provide the same statistics for men, as shown, in Figure 2. There has been a marginally declining trend in years of education, for the urban male cohort, compared to the rural male cohorts. However, the gap between urban and rural cohorts does not seem to decrease dramatically, except for the very young cohorts (age18-20). There are spikes in the trend for very young cohorts because of the small sample size originating from the fact that men marry at an older age than women. In terms of age of marriage, there is a declining trend, perhaps due to sample selection; however, there is little difference in trend between urban and rural cohorts.

Figure 1. Years of Education and Age of Marriage across age cohorts by urban and rural, Women

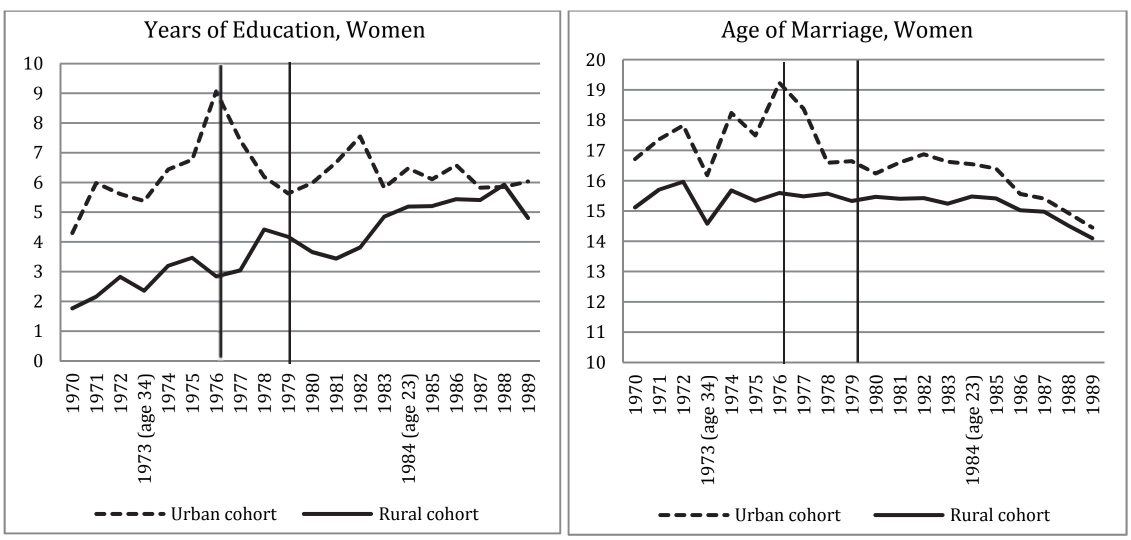
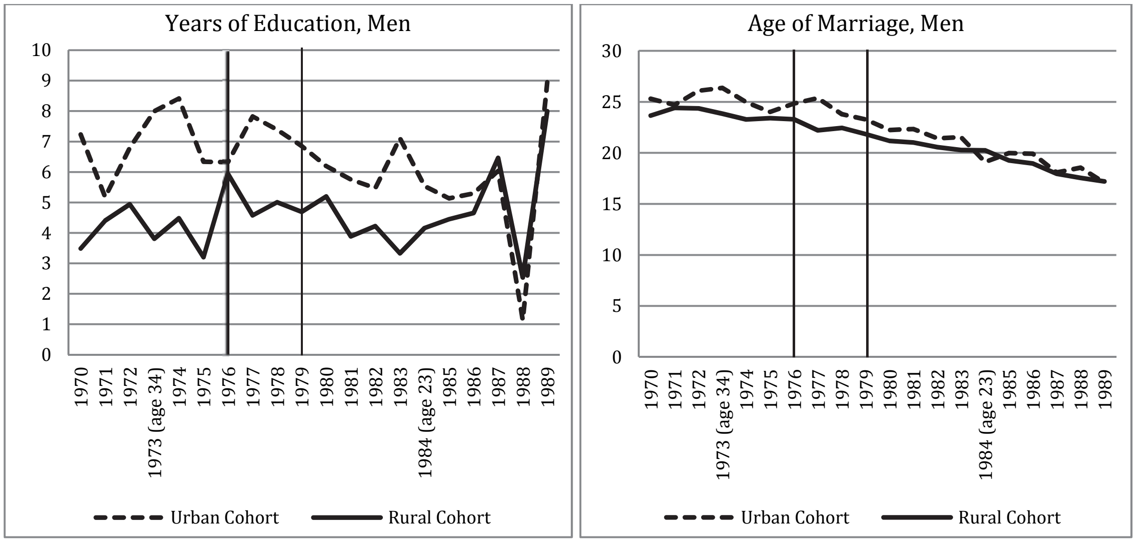


Figure 2. Years of Education and Age of Marriage across age cohorts by urban and rural, Men



In the next subsection, we discuss the identification strategy for the impact of both the free tuition and the FSSAP policies on the years of education, the age of marriage, and labor force participation.

IV. Identification Strategy

We examine the long term impacts of the free tuition policy and the FSSAP using difference-in-difference estimation method by exploiting variation in eligible cohorts, described in Table 2, and geographical variation in policy implementation. The eligibility rule is based on birth year corresponding grade in 1990 and 1994. Four different birth cohorts have been defined: the pre-policy cohort comprises women born before 1976; the free tuition policy cohort is made of women born between 1976 and 1978; the grade 9-10 stipend cohort includes women born between 1979 and 1981; and finally, the grade 6-10 stipend cohort is composed of women born after 1981. The age group of policy cohorts is derived from the mean age of each grade in Household Income and Expenditure Survey in 1995 (Appendix Table 2). Since this study uses the mean age of each grade to define eligible age cohort, it should be noted that there would be potential bias originating from delay in school or repeating grades if the programs have affected the probability of grade repetition or secondary school starting age[36].

Table 2. Eligibility Cohort for Female Tuition and Stipend Program

Grade in 1990	Grade in 1994	Age in 2007	Birth year	Eligible cohort for free tuition, Grade 6 to 8	Eligible cohort for stipend program, Grade 6 to 8	Eligible cohort for stipend program, Grade 9 to 10
11		34	1973	NE	NE	NE
10		33	1974	NE	NE	NE
9		32	1975	NE	NE	NE
8	**12**	**31**	**1976**	**E**	**NE**	**NE**
7	11	30	1977	E	NE	NE
6	10	29	1978	E	NE	NE
5	**9**	**28**	**1979**	**E**	**NE**	**E**
4	8	27	1980	E	NE	E
3	7	26	1981	E	NE	E
2	**6**	**25**	**1982**	**E**	**E**	**E**
1	5	24	1983	E	E	E
	4	23	1984	E	E	E

Note: E stands for eligible cohort and NE refers to the non-eligible cohort.

Using the following specification, we identify the effect of each policy on women's years of education as well as their age of marriage.

$$Y_i = \delta_1 1(FreeTuition) \times Rural_i + \delta_2 1(Stipend, Gr9-10) \times Rural_i + \delta_3 1(Stipend, Gr6-10) \times Rural_i$$
$$+ \delta_4 1(FreeTuition) + \delta_5 1(Stipend, Gr9-10) + \delta_6 1(Stipend, Gr6-10) + \delta_7 Rural_i + \phi g(age_i) + v_i$$

--- Equation 1

The outcome variables are the years of education, the age of marriage, and labor force participation. $1(FreeTuition)$ indicates whether a woman belongs to the free tuition policy birth cohort, $1(Stipend, Gr9-10)$ a dummy for whether a woman is the grade 9-10 stipend birth

[36] Bias from this would be minimal given the fact that there are little impacts on primary schooling years (see falsification test)

cohort, and $1(Stipend, Gr6-10)$ is the indicator for grade 6-10 stipend birth cohort. These birth cohort indicator variables are interacted with $Rural_i$ variable, indicating whether a woman lived in rural areas, at least up to the secondary school entry age (age of 10)[37]. The coefficients of these interaction terms show the effect of each policy: δ_1 captures the effect of the free tuition policy, δ_2 that of the grade 9-10 stipend, and δ_3 that of the grade 6-10 stipend program. Comparison group is the birth cohort born before the implementation of any gender targeted policy. Eligible age cohorts corresponding to each policy are determined according to the schooling age in Bangladesh education system, assuming there is one year delay in school entrance which is based on the mean age of children in each grade in 1990s (Appendix Table 2). Since the analysis is based on the eligibility criteria to treatment (policy) rather than actual treatment, the effects are interpreted as intent-to-treatment (ITT) effects. The age function ($g(age_i)$) is included in the regression to capture the trend in educational attainment or age of marriage, which could have existed even without any policy interventions, due to, for instance, the overall improvement of the education system or secularization. We estimate Equation 1 using three different functional forms ($g(age_i)$); linear function, a quadratic age function, and a piece-wise linear function[38]. We assume that, however, there is no exogenous factor affecting the urban and rural cohorts differentially other than the free tuition policy and the FSSAP[39].

In addition, the model is estimated using two different samples; Panel A uses a sample of married women born between 1989 and 1968 (aged 18 to 39 in 2007), and Panel B uses a sample of women with narrower age band, born between 1984 and 1973 (aged 23 to 34 in 2007), in order to

[37] Two variables are used to create this dummy. One is the duration of current residence and the other is the place where the sampled women migrated from, prior to their current residence.

[38] $g(age_i) = \rho_0(age_i - 34) \times 1(age_i <= 34) + \rho_1 age_i \times 1(age_i > 34)$

[39] There is concern that urban children would have been affected by rising employment opportunity in garment factory during this period. Heath and Mobarak (2012) found that increasing employment opportunity increases the schooling probability of girls. This may potentially bias downward the impacts of the education programs.

make more comparable between the control and treatment age cohorts and to remove potential bias originating from time-varying factors correlated with urban and rural difference in outcomes other than the policy of interest.

Finally, since the primary effects of both programs would lie at the secondary level of education, we restrict the sample to the women with at least primary education[40]. If there is any positive spill-over effect of these programs on primary education (e.g., female students are more likely to finish primary education anticipating the given opportunity to continue their education in secondary school), then restricting the sample may introduce a selection bias. It is, however, shown that this is not the case: there is no effect of these programs on primary level education (Table 6). Next, we first discuss the results using the restricted sample, and then present the results using the full sample.

V. Results

Table 3 shows the impact of the policy on the years of education using the group ineligible for both the free tuition policy and the FSSAP as a control group. The coefficient of the first row measures the impact of the free tuition policy whereas the second and the third row measures the impact of the grade 9-10 stipend program and that of the grade 6-10 stipend program, respectively. The results from Panel A indicate that the free tuition policy did not significantly raise the education level of women. The grade 9-10 stipend program, on the other hand, raised women's education by 1.7 years while the grade 6-10 stipend program increased women's education by 2 years compared to a no policy case. The effects are statistically significant and robust regardless of the functional form of age that controls for the underlying educational trend over time. The estimates using Panel B show similar results, however, the sizes of the coefficients

[40] Black, Devereux, and Salvanes (2005) also restrict their sample to more policy relevant population whom the reform might have affected the most.

are slightly smaller. They correspond to about 1.8 years increases due to the stipend programs. Since both the free tuition and stipend programs only targeted secondary school female students, there should be little impact of the programs on women who had not finished primary education. With the sample of women with at least 5 years of education, the results confirm that the stipend programs did contribute to raising women's education level but the free tuition program did not.

Table 3. Impact of free tuition and FSSAP on years of education

	Panel A: Age 18-49			Panel B: Age 23-34		
	(1)	(2)	(3)	(4)	(5)	(6)
Women of all education level						
Free tuition x rural cohort	0.520	0.487	0.465	0.738	0.803	0.822
	(0.621)	(0.621)	(0.621)	(0.749)	(0.747)	(0.746)
Stipend (grade 9-10) x rural cohort	1.678***	1.599***	1.578***	1.870***	1.873***	1.884***
	(0.495)	(0.492)	(0.491)	(0.611)	(0.610)	(0.610)
Stipend (grade 6-10) x rural cohort	2.042***	1.985***	1.965***	1.831***	1.884***	1.889***
	(0.388)	(0.388)	(0.388)	(0.604)	(0.604)	(0.604)
Age function	no	linear	quadratic	no	linear	quadratic
N	5860	5860	5860	3290	3290	3290
Women with at least 5 years of education						
Free tuition x rural cohort	0.450	0.439	0.535	0.666	0.659	0.674
	(0.621)	(0.622)	(0.618)	(0.674)	(0.673)	(0.675)
Stipend (grade 9-10) x rural cohort	1.565***	1.554***	1.649***	1.830***	1.823***	1.838***
	(0.484)	(0.485)	(0.475)	(0.561)	(0.562)	(0.563)
Stipend (grade 6-10) x rural cohort	1.859***	1.852***	1.970***	1.999***	1.992***	2.007***
	(0.403)	(0.403)	(0.398)	(0.548)	(0.547)	(0.551)
Age function	no	linear	quadratic	no	linear	quadratic
N	2946	2946	2946	1568	1568	1568

Sample: Variables included in the regression but not shown are age cohort dummies of each policy, rural hometown dummy, rural residence dummy, and wealth quintile dummies. Standard errors are clustered at the primary sampling unit. Standard errors are clustered at the primary sampling unit. Significant at 1% level (***), significant at 5% level (**), significant at 10% level (*)

Table 4 shows the impact of both programs on women's age of marriage. Similar to their impacts on the years of education, the free tuition program has not significantly increased the age of marriage while the stipend programs have led to an increase in the age of marriage by about 1.5 years. The size of the effect on the age of marriage is almost the same as the one on the years of education, indicating that keeping female students in school through financial incentives delay their marriage. Marriage is one of the main reasons for girls dropping out of school (Mahmud and Amin, 2006) and the female stipend programs intended for girls to stay in school and unmarried. The results are again robust across the age function specifications and the size of their impacts is slightly larger for the women with more than 5 years of education.

Table 4. . Impacts of free tuition and FSSAP on age of marriage

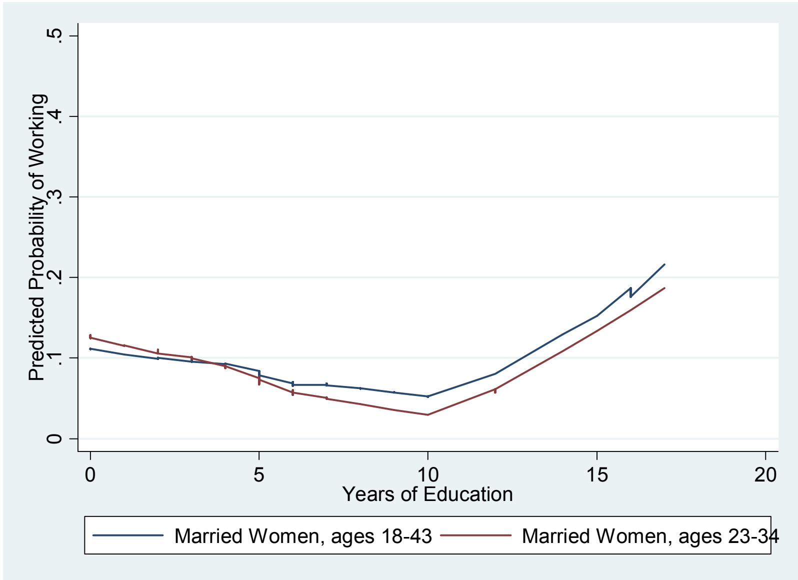
	Panel A: Age 18-49			Panel B: Age 23-34		
	(1)	(2)	(3)	(4)	(5)	(6)
Women of all education level						
Free tuition x rural cohort	0.304	0.324	0.262	0.346	0.345	0.365
	(0.578)	(0.577)	(0.578)	(0.655)	(0.656)	(0.655)
Stipend (grade 9-10) x rural cohort	1.532***	1.582***	1.522***	1.554***	1.553***	1.566***
	(0.451)	(0.453)	(0.450)	(0.531)	(0.531)	(0.530)
Stipend (grade 6-10) x rural cohort	1.432***	1.468***	1.413***	1.105**	1.104**	1.110**
	(0.375)	(0.375)	(0.371)	(0.519)	(0.518)	(0.518)
Age function	no	linear	quadratic	no	linear	quadratic
N	5882	5882	5882	3303	3303	3303
Women with at least 5 years of education						
Free tuition x rural cohort	0.433	0.336	0.476	0.296	0.280	0.338
	(0.837)	(0.838)	(0.834)	(0.906)	(0.905)	(0.902)
Stipend (grade 9-10) x rural cohort	2.108***	2.010***	2.148***	1.991***	1.977***	2.034***
	(0.644)	(0.650)	(0.635)	(0.725)	(0.724)	(0.717)
Stipend (grade 6-10) x rural cohort	2.170***	2.112***	2.284***	1.926***	1.910***	1.970***
	(0.570)	(0.574)	(0.561)	(0.680)	(0.678)	(0.674)
Age function	no	linear	quadratic	no	linear	quadratic
N	2968	2968	2968	1581	1581	1581

Note: Variables included in the regression but not shown are age cohort dummies of each policy, rural hometown dummy, rural residence dummy, and wealth quintile dummies. Standard errors are clustered at the primary sampling unit. Significant at 1% level (***), significant at 5% level (**), significant at 10% level (*).

There is no impact of free tuition on women's labor force participation and this is consistent with the findings on years of education and age of marriage. The impacts of the stipend programs on women's labor force participation are, however, sensitive to selection of samples (Table 5). We find no impacts of the stipend programs for the women of all education level but observe the evidence of increasing women's labor force participation induced by the stipend programs for women with at least five years of education. This would be explained by the non-linear relationship between years of education and women's labor force participation; at much lower levels of education, labor force participation would increase as education level decrease since they have to work to meet subsistence level of consumption, given strong correlation between education level and income; above the subsistence level of consumption, the low returns to upper low to middle levels of education do not compensate for the opportunity cost of working of women (e.g., household's work), therefore, it would be optimal not to work; after reaching the educational attainment where returns to schooling is higher than opportunity cost of working, the likelihood of working would be increasing function of education level since returns to schooling is increasing with higher level of education. This pattern has been documented in existing literatures that look at the relationship between education and labor force participation of South Asian women (Glick and Sahn 1997; Kingdon and Unni, 2001; Das and Desal, 2003; Glick 2008). This pattern is also observed in our analysis (Figure 3). The threshold for increasing labor force participation with higher education is observed to be around 10 years of education. For women with less than 10 years of education (secondary education), the probability working is negatively associated with years of education. However, after having acquired some years of education, their probability of working rises as their education level increases. This means impact of increasing educational attainment on women's labor force participation would exist only after certain level of education achieved, which is the possible channel that the free tuition and stipend programs have had impacted on women's labor force participation.

For women with at least five years of education, having exposed to longer stipend duration (grade 6-10 stipend) increased probability of working by 9 percent, compared to no policy (Pane A in Table 5). Results from Panel B, however, do not show significant impacts of any of the programs on women's labor force participation. This may be because Panel B has smaller sample size, about a half of the sample size compared to Panel A, leading to bigger standard errors, and women in Panel B are at the peak of reproductive age, which potentially interfere the labor force participation, leading to smaller effect size.

Figure 3. Years of Education and Probability of Working



Note: Age, age squared, wealth quintile and geographical residence are controlled.

In order to test whether these increases in educational attainment or in age of marriage are actually induced by the female secondary education policies during this period rather than by an overall improvement of the educational system or/and by the change in perception about women's role in society or by female emancipation movements, we estimate the impact of the policies on the years of education for women with less than grade 5 level of education. If there were differential improvement in the education system in rural areas, primary schooling would also have gone up, however, there is no evidence suggesting this. There is no significant increase in primary schooling years for the free tuition eligible women and there is slight but not significant decrease in primary schooling years for the stipend program eligible women (Table 6). In terms of age of marriage, there is little change in age of marriage, for the free tuition eligible women, while we observe insignificant increase in age of marriage for the grade 9-10 stipend eligible women and insignificant decrease in age of marriage for the grade 6-10 stipend eligible women.

Table 5. Impacts of free tuition and FSSAP on labor force participation

	Panel A: Age 18-49			Panel B: Age 23-34		
	(1)	(2)	(3)	(4)	(5)	(6)
Women of all education level						
Free tuition x rural cohort	-0.019	-0.019	-0.021	-0.031	-0.030	-0.029
	(0.053)	(0.053)	(0.053)	(0.067)	(0.067)	(0.068)
Stipend (grade 9-10) x rural cohort	0.055	0.055	0.053	0.045	0.045	0.046
	(0.049)	(0.049)	(0.049)	(0.066)	(0.066)	(0.067)
Stipend (grade 6-10) x rural cohort	0.038	0.038	0.036	0.026	0.026	0.027
	(0.040)	(0.040)	(0.040)	(0.063)	(0.063)	(0.063)
Age function	no	linear	quadratic	no	linear	quadratic
N	5882	5882	5882	3303	3303	3303
Women with at least 5 years of education						
Free tuition x rural cohort	0.005	0.006	0.010	-0.025	-0.022	-0.022
	(0.076)	(0.076)	(0.076)	(0.090)	(0.091)	(0.091)
Stipend (grade 9-10) x rural cohort	0.086	0.088	0.091	0.059	0.062	0.062
	(0.064)	(0.064)	(0.064)	(0.082)	(0.082)	(0.083)
Stipend (grade 6-10) x rural cohort	0.089*	0.090*	0.095*	0.054	0.058	0.058
	(0.052)	(0.052)	(0.052)	(0.081)	(0.081)	(0.082)
Age function	no	linear	quadratic	no	linear	quadratic
N	2968	2968	2968	1581	1581	1581

Note: Estimation is based on Linear Probability Model (LPM). Variables included in the regression but not shown are age cohort dummies of each policy, rural hometown dummy, rural residence dummy, and wealth quintile dummies. Standard errors are clustered at the primary sampling unit. Significant at 1% level (***), significant at 5% level (**), significant at 10% level (*).

The education trend of men is another counterfactual that would not have been affected by the female education policies. There are, however, literatures addressing that the female stipend programs may have adversely affected boy's education (Fuwa, 2001; Asadullah and Chaudhury, 2009). Therefore, we did not use the male as a comparison group; instead, we investigate whether these programs have indeed adversely affected men's educational attainment. Table 6 shows that this is not the case. The number of years of education of male corresponding cohort of female stipend programs did not decrease; rather, it increased but insignificantly. In terms of marriage, the result from Panel A indicates the grade 6-10 stipend program lead to increased age of marriage for men. Unlike the years of education, the age of marriage, for men, would have been indirectly affected; given that marriage involves both men and women, increasing the age of marriage of women would lead to increased age of marriage, for men. However, the restricted sample, in Panel B, does not show any significant effects of these programs.

Table 6. Falsification Test 1: Women with less than 5 years of education

	Panel A: Age 18-49			Panel B: Age 23-34		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: Years of Education						
Free tuition x rural cohort	0.318	0.315	0.323	0.345	0.346	0.325
	(0.266)	(0.267)	(0.267)	(0.376)	(0.376)	(0.373)
Stipend (grade 9-10) x rural cohort	-0.188	-0.218	-0.214	-0.160	-0.160	-0.171
	(0.239)	(0.236)	(0.237)	(0.356)	(0.357)	(0.354)
Stipend (grade 6-10) x rural cohort	-0.127	-0.132	-0.122	-0.110	-0.108	-0.103
	(0.188)	(0.185)	(0.187)	(0.357)	(0.358)	(0.355)
Dep. Var.: Age of Marriage						
Free tuition x rural cohort	0.082	0.085	0.068	0.006	-0.003	-0.026
	(0.558)	(0.559)	(0.559)	(0.729)	(0.727)	(0.723)
Stipend (grade 9-10) x rural cohort	0.173	0.211	0.200	0.081	0.082	0.071
	(0.515)	(0.514)	(0.513)	(0.697)	(0.697)	(0.694)
Stipend (grade 6-10) x rural cohort	-0.313	-0.307	-0.331	-0.789	-0.797	-0.792
	(0.383)	(0.382)	(0.380)	(0.656)	(0.654)	(0.654)
Dep. Var.: Labor Force Participation						
Free tuition x rural cohort	-0.060	-0.060	-0.063	-0.062	-0.068	-0.063
	(0.083)	(0.083)	(0.083)	(0.112)	(0.112)	(0.112)
Stipend (grade 9-10) x rural cohort	0.007	0.008	0.006	0.006	0.007	0.010
	(0.074)	(0.075)	(0.075)	(0.105)	(0.105)	(0.106)
Stipend (grade 6-10) x rural cohort	-0.014	-0.014	-0.018	-0.022	-0.028	-0.029
	(0.064)	(0.064)	(0.064)	(0.108)	(0.108)	(0.108)
Age function	no	linear	quadratic	no	linear	quadratic
N	2914	2914	2914	1722	1722	1722

Note: Regression uses Panel A sample. Variables included in the regression but not shown are age cohort dummies of each policy, rural hometown dummy, rural residence dummy, and wealth quintile dummies. Standard errors are clustered at the primary sampling unit. Significant at 1% level (***), significant at 5% level (**), significant at 10% level (*).

Table 7. Falsification Test 2: Impacts on Men's education, age of marriage and LFP

	Panel A: Age 18-49			Panel B: Age 23-34		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: Years of Education						
Free tuition x rural cohort	0.043	0.016	0.016	0.519	0.527	0.547
	(0.620)	(0.620)	(0.620)	(0.779)	(0.779)	(0.779)
Stipend (grade 9-10) x rural cohort	0.103	0.077	0.077	0.558	0.569	0.597
	(0.512)	(0.511)	(0.510)	(0.688)	(0.685)	(0.686)
Stipend (grade 6-10) x rural cohort	0.472	0.447	0.447	0.394	0.403	0.443
	(0.437)	(0.438)	(0.438)	(0.678)	(0.678)	(0.682)
Age function	no	linear	quadratic	no	linear	quadratic
N	3765	3765	3765	1248	1248	1248
Dep. Var.: Age of Marriage						
Free tuition x rural cohort	0.036	0.013	0.018	-0.669	-0.646	-0.637
	(0.453)	(0.454)	(0.452)	(0.583)	(0.582)	(0.582)
Stipend (grade 9-10) x rural cohort	0.428	0.405	0.415	-0.311	-0.276	-0.263
	(0.411)	(0.411)	(0.404)	(0.587)	(0.578)	(0.579)
Stipend (grade 6-10) x rural cohort	1.029***	1.006***	0.968***	0.210	0.245	0.262
	(0.367)	(0.371)	(0.346)	(0.570)	(0.569)	(0.570)
Age function	no	linear	quadratic	no	linear	quadratic
N	3770	3770	3770	1251	1251	1251
Dep. Var.: Labor Force Participation						
Free tuition x rural cohort	0.017	0.017	0.017	0.017	0.017	0.017
	(0.020)	(0.020)	(0.020)	(0.028)	(0.028)	(0.029)
Stipend (grade 9-10) x rural cohort	-0.016	-0.016	-0.016	-0.009	-0.009	-0.009
	(0.017)	(0.017)	(0.017)	(0.024)	(0.024)	(0.024)
Stipend (grade 6-10) x rural cohort	-0.012	-0.013	-0.013	-0.007	-0.007	-0.007
	(0.017)	(0.017)	(0.017)	(0.029)	(0.029)	(0.029)
Age function	no	linear	quadratic	no	linear	quadratic
N	3770	3770	3770	1251	1251	1251

Note: Sample includes men with at least 5 years of education. Variables included in the regression but not shown are age cohort dummies of each policy, rural hometown dummy, rural residence dummy, and wealth quintile dummies. Standard errors are clustered at the primary sampling unit. Significant at 1% level (***), significant at 5% level (**), significant at 10% level (*).

VI. Conclusion

This study finds that gender targeted conditional cash transfer program implemented in 1994 in Bangladesh has contributed to raising women's years of education by 1.6 to 2 years while the free tuition policy did not lead to any significant impact on their years of education. However, unlike existing literatures, which suggest negative effect of female secondary stipend program on boys' school enrollment, we do not find any decrease in boys' years of education due to the program. Furthermore, the stipend program has led to an increase in the age of marriage of women by 1.4 to 2.3 years; there is also some evidence that the age of marriage of men has gone up as a result of the stipend program. We have also documented some evidence that stipend program leads to an increase in the labor force participation of married women.

This study contributes to the existing literatures by documenting the long term impacts of gender targeted education policies. Furthermore, this paper evaluates, not only the impacts of these policies on years of education and women's labor force participation, but it also investigates the extent to which they have led to delayed marriage for women, with potentially non negligible benefits for educated women as well as for the Bangladesh economy and society at large.

In South Asia, it is well documented that there is U-shaped relationship between education and labor force participation. This study empirically confirms the suggestion of existing literatures, that is, in order to improve the economic participation of women in society, policies promoting higher level of education for girls should be implemented, as they would generate the intended impacts. In contrast, policies focusing exclusively on providing basic education would not produce the direct economic benefits for households and society at large, although some indirect intergenerational impacts such as better child health and education could stem from them.

While the impacts of demand side interventions such as the female tuition and stipend policies are solidly established on female labor force participation through our study, it is worth bearing in mind that, this increased female labor participation would unlikely occur, in the absence of economic opportunities for women in the country. In Bangladesh, the needs of a rapidly growing garment industry in which over 85 percent of the workers are female, are being met by the increased supply of educated female workers whose returns to education and opportunity cost of not working have substantially increased due to the gender targeted education policies of the 1990s.

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Appendix

Appendix Table 1. Coverage of Female Stipend Program

Year	Total No. Secondary School (excl. Madrasah)	No. of Institution received stipend (incl. Madrasah)	No. of female students received stipend
1994	11,488	12,713	70,886
1995	12,012	14,119	1,409,382
1996	12,978	16,722	2,300,062
1997	13,778	17,847	2,825,350
1998	14,518	18,721	3,198,559
1999	15,460	18,788	3,564,404
2000	15,720	19,919	3,961,194
2001	16,166	21,027	4,191,058
2002	16,562	22,893	4,193,352
2003	17,386	23,719	3,467,123
2004	18,267	24,950	2,356,856
2005	18,500	25,425	2,270,343

Source: Bangladesh Educational Statistics, 2006

Appendix Table 2. Mean Age by grade in 1995

	Age	
Grade	Mean	Std dev.
1	7.3	2.7
2	8.5	1.8
3	9.7	1.9
4	10.6	2.4
5	11.4	1.7
6	12.3	1.8
7	13.1	1.6
8	14.1	1.7
9	15.3	3.0
10	16.4	2.5

Data source: Household Income and Expenditure Survey,1995

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