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ABSTRACT

Household Preferences and Child Labor in Rural Ethiopia*

This paper revisits the causes behind child labor supply by focusing on an aspect that has received little attention: the link between the household head's risk and time preferences and observed child labor supply. We develop a theoretical model and empirically test for this causality using data from the seventh round of the Ethiopian Rural Household Survey. We find child labor to be increasing in both higher adult discount rates and higher degrees of risk aversion, and this finding is robust across alternative empirical approaches. Higher discount rates favor current consumption which is financed in part by child labor income while high risk aversion to future income (due to either low or uncertain returns to education) favor child labor at the expense of schooling.

JEL Classification: C93, J43, O55

Keywords: risk and time preferences, education, child labor, Ethiopia

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1. Introduction

Global efforts notwithstanding, child labor remains pervasive in the developing world[1]. The literature on the causes, consequences and policies to eliminate child labor is vast, and well established. The supply of child labor is primarily related to poverty (Basu and Van, 1998), failure to internalize the benefits of education (Baland and Robinson, 1999), credit constraints (Grote, Basu and Weinhold, 1998; Ranjan, 2001), debt bondage (Basu and Chau, 2003 and 2004) and stigma (Patrinos and Shafiq, 2008). The consequences of child labor include impaired childhood development, low educational attainment and fewer gainful employment opportunities as adults which perpetuates the vicious cycle of poverty (Beegle et al, 2009). Policy prescriptions to eliminate child labor range from conditional cash transfers, enforcement of adult minimum wage laws, education subsidies, access to credit and social labelling programs (Bourguignon, Ferreira and Leite, 2003, Basu, 2000; Ravallion and Woden, 2000; Basu, Chau and Grote 2004 and Di Maio and Fabbri (2013)).

In this paper, we revisit the *causes* behind the existence of child labor by focusing on an aspect yet to be explicitly analyzed in the literature: the role of adult risk and time preferences on the extensive (whether a child works) and intensive (number of hours worked) margin of child labor supply. Aside from the fact that this is an under researched topic in itself, our interest in this issue is guided by recent papers that have analyzed the impact of parental or household head's risk and time preferences on children's educational outcomes (Sovero, 2017; Tanaka and Yamano, 2015; Tabetando, 2019). This link between adult behavioral preferences and investment in child education offers rudimentary insight into the link between behavioral preferences and child labor supply since the trade-off between child labor and schooling is well documented and extensively researched. For example, the literature on the impact of government run conditional cash transfer programs in Latin America and in parts of Africa which incentivizes school attendance for children from poor households at the expense of child labor supply offers conclusive evidence on how

[1] According to the International Labour Organization (ILO), 168 million children in the 5-17 age group work as child laborers worldwide (ILO, 2015). The incidence is highest in Sub-Saharan Africa with 21% (59 million child laborers), followed by 9.3% in Asia and the Pacific (78 million child laborers), 8.8% in Latin America and the Caribbean (13 million child laborers) and 8.4% in the Middle East and North Africa (9.2 million child laborers). ILO statistics also identify the majority of child laborers as working in the agricultural sector globally (59% or 98 million child laborers).

closely the demand for education and the supply of child labor are connected (de Hoop and Rosati, 2013). Intuitively, therefore, the observed effect of household risk and time preferences on child labor supply should be orthogonal to the effect of these same preferences on child educational outcomes reported in recent research.

Three recent papers analyzing adult risk and time preferences on investment in child education arrive at broadly similar conclusions. Sovero (2017) uses the Mexican Family Life Survey to find that risk averse parents spend more resources to prioritize schooling for boys over girls[2]. Tanaka and Yamano (2015) uses data from a field experiment in rural Uganda to analyze the impact of the risk aversion and patience profile of the household head on various schooling related variables. They find that household heads with higher patience rates prioritize children's education. Further, risk aversion of the household head delays school enrollment of young children, especially boys. Tabetando (2019) combines field experiments with longitudinal household data, also from rural Uganda, to find that overall risk averse parents invest more in child education as proxied by per school age child educational expenditure. However, there is a negative association between parental risk aversion and child educational investment for poorer households. Indeed, if the supply of child labor is inversely related to the demand for education then the above findings would imply that (i) relatively more patient parents/household heads are less likely to send their children to work and (ii) relatively more risk averse parents/household heads are more likely to send their children to work. Our empirical analysis, using data from the Ethiopian Rural Household Survey, confirms these hypotheses. While our result relating time preferences to child labor supply is intuitive, the finding that risk aversion is positively associated with child labor supply is nuanced and requires elucidation.

Two possible pathways can explain the positive association between parental risk aversion and child labor supply. First, rural household heads whose primary occupation is farming might prefer the use of family labor (including child labor) to lower on-farm monitoring costs. As Bhalotra and Heady (2003) finds for rural Pakistan, richer households who hire outside labor can land up saving on monitoring costs by engaging household child labor on own farms – a finding

[2] Sovero (2017) also finds that a mother and father's risk aversion have negative effects on their daughter's weight and BMI, but positive effects on their son's weight and BMI.

since confirmed by Lima, Mesquita and Wanamaker (2015). Interestingly, if child labor and education are the only two alternatives for rural households, this 'wealth paradox', identified by Bhalotra and Heady and Lima et.al., can also be observed if education yielded uncertain returns and the utility function of the household heads exhibited increasing relative risk aversion (IRRA) – i.e., an increase in wealth reduces the fraction of wealth invested in the risky asset. Our results do not grant support to either of these pathways on account of (i) the differences in context, particularly the fact that the vast majority of Ethiopian farmers operate relatively small (and by default-family operated) plots of land as compared to the larger Asian land holdings and Latin American plantations analyzed respectively by Bhalotra and Heady (2003) and Lima et. al. (2015) and (ii) the risk profiles used in our empirical analysis is extrapolated under the assumption of a constant relative risk aversion (CRRA) utility function, and we find that wealth (either land size or livestock value) has no effect on child labor supply in rural Ethiopia. Second, as Tabetando (2019) identifies, credit constraints might impede investments in child education and bias a household's decision in favor of child labor. However, in the Ethiopian setting, a vast majority of children combine school with work which might indicate that credit constraints are not as binding as in the Ugandan context. Instead, we explore a third alternative where investment in a child's education acts as insurance for parents in old age but the returns to education is a risky. In this setting, risk aversion to the returns from schooling gives rise to a combination of schooling and child labor as opposed to corner solutions where children exclusively devote their non-leisure time to either one of these two activities.

The rest of the paper is organized as follows. Section 2 offers a theoretical model that pins down the relationship between adult behavioral preferences and the child labor-schooling trade-off. Section 3 explains the data, presents descriptive statistics and discusses the risk and time experiments. Section 4 outlines the empirical strategy, Section 5 reports the results while Section 6 offers additional tests that confirm our theoretical conjectures. Section 5 concludes.

2. Theory

We consider a stylized economy comprised of a finite number of households. Each household consists of an adult and a child. The adult maximizes household utility over two periods as follows: In the first period, household utility depends on the level of consumption (adult and the child's combined) and the number of hours spent in school by the child. In the second period, household utility depends solely on the income generated via the investment in child education in the period prior. In other words, second period consumption is financed entirely by the income earned by the child who is now an adult in this period. We write the inter-temporal utility function as[3]:

$$U_t = \alpha C_t + (1-\alpha)s_{kt} + \frac{1}{(1+r)}\frac{Y_{t+1}^{(1-\theta)}}{(1-\theta)} \qquad (1)$$

Thus, utility in period (t) consists of (i) the weighted sum of consumption (C_t) and the utility from child education (s_{kt}) in the first period with $\alpha \in [0, 1]$ as the weight given to current consumption vis-à-vis child schooling (thus, $(1-\alpha)$ also captures parental altruism) and (ii) the discounted utility in the second period ($t+1$) exhibiting constant relative risk aversion (CRRA) in income. In equation (1) above, s_{kt} is the number of hours spent the child in school, r is the discount rate and θ ($\theta > 0$; $\theta \neq 1$) is the measure of risk aversion (with higher values of θ indicating higher risk aversion).

We next turn to the budget constraints. In period t consumption is financed by the sum of adult's income (Y_t) and income from child labor ($w_{kt}l_{kt}$) net of expenses incurred for the child's education (βs_{kt}). Here w_{kt} is the child wage per hour and l_{kt} is the number of hours spent working by the child while β as the cost of schooling per hour. Formally,

$$C_t = Y_t + w_{kt}l_{kt} - \beta s_{kt} \qquad (2)$$

Since the time spent working and the time spent in school must add up to the total number of non-leisure hours for the child (T), we have a binding constraint[4]

$$s_{kt} + l_{kt} = T \qquad (3)$$

In period ($t+1$), consumption is solely financed by the income of the now grown up child (Y_{t+1}). This income in turn depends on the amount of education acquired by the child in period t

[3] Our model is a variant of Basu and Chau's (2003) model of child labor in debt bondage and Tabetando's (2019) model relating adult risk aversion to child education.

[4] Note that as long as the returns to education (Y_{t+1}) and the child wage (w_{kt}) are positive we can rule out corner solutions where a child exclusively works or goes to school. In effect, this model guarantees an interior solution where children combine work with schooling.

and other exogenous factors (labor market conditions) in $t+1$ (A_{t+1}). We assume here that $A_{t+1}$is uncertain such that $A_{t+1} = pA_{low} + (1-p)A_{high}$, where $0 < p < 1$ is the probability that A takes on a low value, A_{low}. In effect, investment in education in the current period is both an insurance in old age as well as an investment in a risky asset. We assume a simple Cobb-Douglas functional form for income in $t+1$ as

$$Y_{t+1} = s_{kt}^{\delta} A_{t+1}^{(1-\delta)};\ 0 < \delta < 1, A_{t+1} > 0 \tag{4}$$

We define the discount factor (ρ) as $\rho = \frac{1}{(1+r)}$ and $\sigma = 1 - \theta$. Equation (1) is then re-written as

$$U_t = \alpha C_t + (1-\alpha)s_{kt} + \rho \frac{Y_{t+1}^{\sigma}}{\sigma} \tag{5}$$

Substituting equations (2), (3) and (4) into equation (5), we have

$$U_t = \alpha[Y_t + w_{kt}(T - s_{kt}) - \beta s_{kt}] + (1-\alpha)s_{kt} + \frac{\rho}{\sigma}(s_{kt}^{\delta} A_{t+1}^{(1-\delta)})^{\sigma} \tag{6}$$

Maximizing U_t with respect to the time spent in school by the child s_{kt} yields the first order condition below,

$$\frac{\partial U_t}{\partial s_{kt}} = [1 - \alpha(1 + w_{kt} + \beta)] + \frac{\rho\delta}{s_{kt}}[Y_{t+1}]^{\sigma} = 0 \tag{7}$$

To understand the relation between the time spent in school by the child and the adult's patience and risk aversion parameters we totally differentiate equation (7) above[5] to get.

$$\frac{\partial s_{kt}}{\partial \rho} = -\frac{1}{\rho}\frac{s_{kt}}{((\sigma-1)-(1-\delta)Y_{t+1})} > 0 \tag{8}$$

$$\frac{\partial s_{kt}}{\partial \sigma} = -\frac{s_{kt}\, log Y_{t+1}}{((\sigma-1)-(1-\delta)Y_{t+1})} > 0 \tag{9}$$

[5] We use a log transformation of equation (7) which generates $\log[\alpha(1 + w_{kt} + \beta) - 1] = \sigma \log \frac{\rho\delta}{s_{kt}} Y_{t+1}$ before differentiation to simplify the derivations.

Given $\sigma - 1 = -\theta$, the denominator is negative for both equations (8) and (9). Since $\rho = \frac{1}{1+r}$, equation (8) shows that as the discount rate rises the child gets to spend less time in school and more in time in child labor. The reasoning is intuitive: a higher discount rate (i.e., higher impatience) means that the adult has a higher preference for current as opposed to future consumption. Since future consumption is entirely dependent on the human capital acquisition by the child, a relatively more impatient adult ends up investing less in child education.

With $\sigma = 1 - \theta$, equation (9) shows that higher risk aversion implies lower investment in education and a higher preference for child labor. This is because the adult exhibits risk aversion with respect to income in the second period, and a relatively more risk-averse adult would favor current income - which includes the income earned by the child as a laborer – over future income generated via investment in child education. It can be questioned whether risk aversion with respect to future income (or in this context, the returns to child education) is realistic in the context of rural Ethiopia (or for that matter any developing economy). With a variety of labor market imperfections (including high search costs, low returns and weak labor laws) in developing countries - especially in Sub-Saharan Africa, we argue that risk aversion to future returns to education is realistic. Effectively, the child labor-schooling decision for a household head can be viewed as a gamble with child labor as the safe option and education as the lottery.

3. Data

Our empirical analysis is based on the 7th round of the Ethiopian Rural Household Survey, conducted in 2009. This panel survey initiated in 1989 within 6 villages in Central and Southern Ethiopia. Extended follow up surveys - with 15 more villages added - were conducted in 1994, 1995, 1997, 2004 and 2009. We restrict our analysis to the latest cross-section in 2009 since the module exploring household preferences is only available for this wave of data collection. The data collected in this 7th round is representative of the agro-climatic zones of the country. The selection of districts and households within districts is based on stratified sampling. The survey includes 1577 households and 7096 individuals from 21 peasant associations[6].

[6] Data is collected in 4 out of the 9 regions in the country, which are representative for the agro-climatic zones: Tigray, Amhara, Oromia and SNNP (Southern Nations, Nationalities and People's Region). Each region is further divided into altogether 15 zones, which in turn are divided into Woredas. The smallest

Of special interest to us are the child/youth labor module, and the module on household preferences. The child/youth labor module is conducted for individuals aged 4-21 and collects information on typical hours of work supplied per week and contains detailed questions on education, including starting time, degrees obtained as well as any discontinuity. Most questions are aimed at acquiring information for the preceding 12 months. Given that less than 1% of the children in the sample reported any work outside of the household farm and within the household, we exclude this group from our analysis. Consequently, we first conduct our baseline analysis based on the hours of work for the sample as a whole and folow up by scrutinizing whether child laboer in either of the two reported categories – farm work and domestic activities – alter the baseline results[7].

For consistency with the literature on child labor and schooling, we restrict our sample to children within the 7-15 age bracket. Setting the lower bound at age 7 reflects the fact that formal schooling in Ethiopia begins at this age, even though it is not necessarily always legally binding (Haile and Haile, 2012). The age bracket is also consistent with the Minimum Age Convention of the ILO, whereby children should not be expected to work below the age of 15. After accounting for missing observations and outliers[8] in the hours of work reported, we are left with a sample of 2337 child observations.

Before exploring the socio-economic characteristics of our sample, we explain how the key explanatory variables of interest to us, namely risk and time preferences[9] are imputed. Questions within this experimental module are answered by the household head in 95.77% of the cases. In the remaining 4.23% a different household member completed the questionnaire. In our empirical analysis we control for characteristics of the key respondent, including gender and whether the child concerned is his or her biological child or grandchild. As a robustness check we excluded respondents who were not the head of household but were acting as a proxy at the time of the

(rural) administrative unit is the Peasant Association. The survey includes 21 Peasant Associations. This is an administrative unit that consists of several villages.

[7] Evidence suggests that non-farm related tasks such as domestic work performed by children can be equally arduous and debilitating as work on the farm (Dinku, Fielding and Genς 2019).

[8] We exclude observations of more than 56 working hours a week, which would have indicated that children work for more than 8 hours a day in a 7-day week. Excluding these outliers does not affect our analysis.

[9] We thank Tung Dang for excellent research assistance with this module in the 7th round of the Ethiopian LSMS survey.

survey. Since this exercise did not influence our results, we chose to base our analysis on the full sample of respondents. The assessment of risk preferences is based on the Eckel and Grossman (2002) elicitation method with adjustment of the vocabulary such that local farmers better understand the options[10].

The codification of risk-taking behavior is based on the following question:

- *"Now imagine that you are going to the market to sell a bag of maize. Would you prefer:*

  (a) To be certain you will receive 250 Birr for one bag;

  (b) Have an equal chance that you will be paid 200 Birr or 400 Birr;

  (c) Have an equal chance to be paid 150 Birr or 550 Birr,

  (d) Have an equal chance to be paid 100 Birr or 700 Birr,

  (e) Have an equal chance to be paid nothing or 1000 Birr."

Note that the gambles (a) to (e) above are successively increasing in their payoffs as well as in the levels of riskiness as indicated by higher standard deviations. Based on an individual's choice among the gambles (and assuming that choices are rational and consistent), we can identify the range within which an individual's coefficient of relative risk aversion falls (Kimball, Sahm and Shapiro, 2008). Assuming a utility function that exhibits constant relative risk aversion (CRRA) of the form $u(Y) = \frac{Y^{1-\theta}}{1-\theta}$. Ignoring wealth outside of the experiment, and assuming that initial wealth is zero for all individuals, the following condition must hold for all individuals who choose gamble (e) over gamble (d) (and therefore gambles (a), (b) and (c)): $0.5\frac{0^{1-\theta}}{1-\theta} + 0.5\frac{10^{1-\theta}}{1-\theta} > 0.5\frac{1^{1-\theta}}{1-\theta} + 0.5\frac{7^{1-\theta}}{1-\theta}$. Solving for $\theta = 0.33$ gives us the CRRA threshold that makes individuals indifferent between gambles (d) and (e)[11]. In similar fashion, the value of θ that makes an

[10] There is a consensus in both the broader experimental literature and the literature focusing on developing countries that this method is preferable to alternatives such as Holt and Laury (2002) due to its simplicity and lower risk of misunderstanding by participants (Corsetto and Filippin, 2016; Charness and Viciesza, 2016). For example, Charness and Viciesza (2016) present evidence from Senegal that the Holt-Laury (2002) routine was poorly understood by relatively less educated subjects. Moreover, Dasgupta et.al. (2019) show a high level of internal consistency between the results based on the Eckel-Grossman (2002) mechanism and an investment task.

[11] Note that in the calculations the payoffs are scaled by 100 without any loss of generality, and θ is solved using Matlab.

individual indifferent between gambles (c) and (d) equals 0.68, and so on. Table 1 summarizes the range of CRRA associated with each of the gambles.

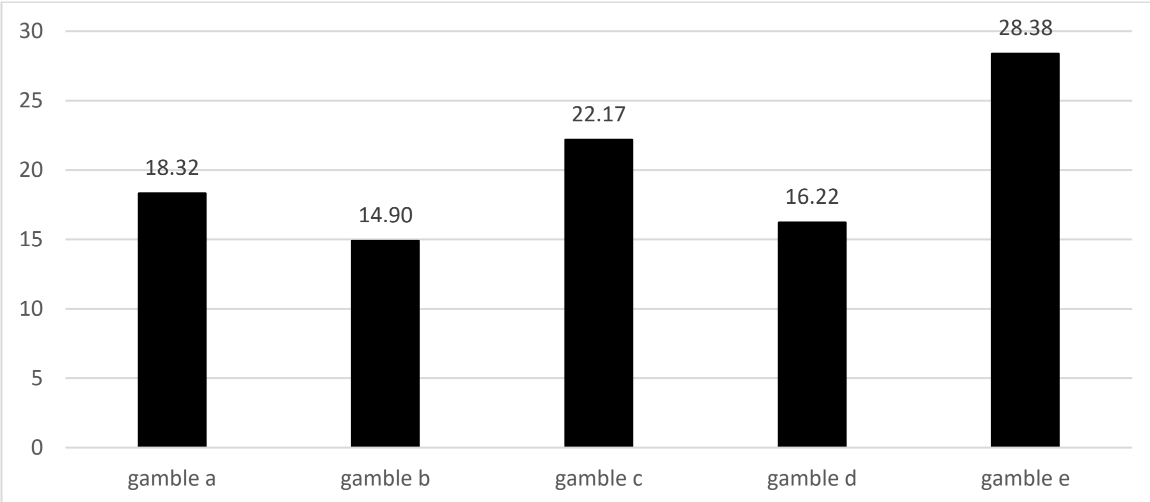
Table 1: Implied CRRA range for the experiment on risk preferences

Choice (50/50 Gamble)	Low payoff	High payoff	Expected return	Standard deviation	Implied CRRA range	Degree of risk aversion
Gamble (a)	250	250	250	0	$\theta > 3.25$	Highest
Gamble (b)	200	400	250	100	$1.10 < \theta < 3.25$	High
Gamble (c)	150	550	250	200	$0.68 < \theta < 1.10$	Medium
Gamble (d)	100	700	250	300	$0.33 < \theta < 0.68$	Low
Gamble (e)	0	1000	250	500	$\theta < 0.33$	Lowest

Figure 1 below highlights the distribution of risk profiles within the sample. Close to 29% of the respondents are concentrated in the highest risk category, 22% in the medium risk category while less than 19% of the respondents are concentrated in the lowest risk category[12].

[12] In Figure 1, gamble (a) is the least risky (To be certain you will receive 250 Birr for one bag) while gamble (e) is the most-risky (Have an equal chance to be paid nothing or 1000 Birr).

Figure 1: Distribution of Responses to the Question on Risk Taking Behavior, % of total



What explains this high a proportion of high-risk takers in our sample? While the focus of our analysis is on the impact of adult behavioral preferences on child labor and education outcomes, adult behavioral preferences are endogenous to several adult-specific variables namely, age, income, education and own childhood experiences. While analyzing the determinants of adult risk and patience profiles are beyond the scope of this paper, we offer some insights into the link between an individual's education and risk aversion gleaned from a few studies undertaken in the developed and developing world. Noting that robust estimation of the causality between education and risk aversion is complicated by the fact that (a) an exogenous shock to education (changes in educational policy) is needed to identify the direction of the causality and (ii) the education-risk aversion link is influenced by the underlying assumption on whether the utility function exhibits constant, increasing or decreasing risk aversion, the consensus is that in developed countries education and risk aversion are negatively related. As examples, Belzil and Leonardi (2013) asks the question of whether education is a risky investment or insurance using data from the Bank of Italy and find that risk aversion acts as a deterrent for higher education. Black et.al (2018) using Swedish data finds that estimate the effect of education on stock market participation and on the share of financial wealth invested in stocks, conditional on participation and finds that education and risk aversion are negatively related. Hryshko et.al. (2011) uses US data to find that a policy-induced increase in the high school graduation rate leads to significantly lower number of individuals being highly risk averse in the next period. However, in a developing country context, Chong and Martinez (2019) using artefactual experiments in Peru finds that additional years of education increases risk aversion[13]. A systematic analysis as to why education has such opposite effects on risk aversion in developed versus developing countries is yet to be undertaken but our study offers a possible clue: the education-risk aversion link may well be influenced by how uncertain the returns to education are deemed to be. In our sample, however, there is little evidence of education influencing risk aversion possibly due to low overall education levels. Specifically, 54.67% of adults with no education are risk averse while 45.33% are risk takers while amongst adults with some education, 55.89% are risk averse while 44.11% are risk takers.

Two other reasons might explain the large proportion of high-risk takers in our sample. First, evidence from a wide range of contexts points to men revealing greater preference for risk than women (Harris et.al. 2006), hence it is plausible that the higher proportion of households exhibiting risk-taking behavior can be attributed to the fact that respondents to the experiments in Ethiopia were largely male head of households[14]. Second, the design of the risk experiment – which does not involve losses to the respondent in any of the gambles (a) through (e) – might have induced greater risk taking. Yesuf and Bluffstone (2009) through their risk experiments in the Ethiopian highlands found that individuals were likely to be more risk averse when the gambles involve both gains and losses as compared to gambles involving gains only.

For the purposes of our empirical analysis, we define a ***high-risk taker*** variable which assigns a value of one to the choice of gambles (d) and (e) and zero otherwise. In other words, respondents who opt for riskier choices than the risk neutral gamble (c) are considered high-risk takers. In empirical analysis, there is no established rule with regards to coding the risk aversion parameter generated via the Eckel and Grossman (2002) experiment. As an alternative, Dasgupta et.al. (2019) experiment with a continuous *risk coefficient* variable based on the lower bound, upper bound and the mid-point in the risk-preference ranges highlighted in Table 1. This approach poses the problem of assigning a concrete value in the open intervals associated with gambles (a) and (e), and as a result this method has the potential to generate conflicting results depending on

[13] Cardenas and Carpenter (2008) provides an excellent survey of field experiments in developing countries that aims to uncover whether utility functions exhibit constant, decreasing or increasing risk aversion.
[14] The proportion of individuals in our high-risk category exceeds that estimated by Dasgupta et.al. (2019) where slightly more than 18% of subjects (laboratory experiment in India) opted for the highest risk gambles, as well as those of Crosetto and Filippin (2016) where 20% of the subjects (laboratory experiment in Germany) picked gamble (e).

the values chosen. Therefore, to avoid confusion, we use the dummy capturing a high-risk taker in our analysis[15].

We use two questions in the module on household preferences to capture the time discount rate (patience level) of the respondent.

Question 8 in the questionnaire:

- "*Would you prefer to be given (a) 100 Birr in one month, or (b) 125 Birr in two months*." It takes the value of 0 if the respondent picks answer (a).

Question 9 in the questionnaire:

- "*Would you prefer to be given (a) 100 Birr in one month, or (b) 150 Birr in two months.*" It takes the value of 0 if the respondent picks answer (a).

Figure 2 shows the distribution of responses to the two questions above. As expected, in the majority of cases (80% in the first case and 70% in the second) individuals opted for instant gratification. The rates are consistent with time preferences estimates from less developed countries, such as those found by Bauer and Chytilová (2010) for rural Uganda. As in the case for risk aversion, we check whether adult education levels have an influence on their patience profiles. However, unlike Jung, Bharati and Chin (2019) who finds education having a positive influence on patience in Indonesia, we do not observe any correlation in our sample. Amongst household heads with no education, 36.2% are patient and 63.8% are impatient, while amongst household heads with some education, 36.27% are patient and 63.73% are impatient.

[15] We experimented with the Dasgupta et. al. approach, assigning 3.25 in the case of gamble (a) and 0.10 (an arbitrary value less than 0.33) in the case of gamble (e). The empirical analysis based on this coding strategy supports our theoretical prediction, even though moving towards the lower bounds of the intervals in Table 1 reduces the significance of our results. In either case, when we estimate a threshold model based on these continuous risk coefficient variables, the model defined the threshold as 0.33 (i.e., the lower bound for gamble (d)) when the continuous risk coefficient was based on the lower bound of the intervals and 0.68 (i.e., the lower bound for gamble (c)) when it was based on the higher bounds of the intervals. This gives further numerical credence to our choice of gamble (d) as the cut-off point that defines a ***high-risk taker***.

Figure 2: Answers to Time Preference Questions

We assume that utility is time-separable and takes the following stationary form: $U(c_t, c_{t+k}) = u(c_t) + \delta^k u(c_{t+k})$ where the period specific utility takes the liner form $u(c) = c$, which implies $\delta \approx \left(c_t/c_{(t+k)}\right)^{(1/k)}$. The intertemporal discount rate, IDR, is thus defined as: $IDR = 1/\delta - 1$, with a higher IDR implying a greater degree of impatience (Tanaka, Camerer, and Nguyen, 2010). Focusing on questions 8 and 9 on the survey, which respectively asks respondents to choose between two amounts, we can estimate the IDR by assuming that transaction costs involving future choices are zero. The respective calculations are shown in Table 2A.

Table 2A: Calculating Indifference Discount Factors

	t=30	t=60	'Indifference' discount factor (ô)	Indifference' discount rate (IDR)
Question 8	100	125	0.993	0.007
Question 9	100	150	0.987	0.014

Once the IDR is estimated, we can use the specific choices to each of the questions - 8a, 8b, 9a and 9b respectively - to extrapolate the patience level of a respondent in Table 2B.

Table 2B: Assigning individuals to time preference categories

Choices	Implied discount factor range	Implied discount rate range	Patience level
8a & 9a	< 0.987	IDR > 0.014	Least patient
8a & 9b	0.987 < < 0.993	0.007 < IDR < 0.014	Medium patient
8b & 9a	-	-	-
8b & 9b	> 0.993	IDR < 0.007	Most patient

For our empirical analysis, we define a "least_patient" variable that takes the value of 1 if the respondent chose options 8a and 9a while a value of 0 is assigned to all those who did not pick 8a and 9a as their response. A "medium_patient" variable takes on the value 1 if the options 8a and 9b are chosen and 0 otherwise. Finally, a "highly_patient" variable captures those respondents picking options 8b and 9b with value 1 while a value of 0 is assigned to all others.

Table 3 reports descriptive statistics for our variables of interest. We observe that on average 64% of the children supplied labor on the family farm during the reference period, while approximately 77% were involved for at least a few hours a week in domestic work. Of those children engaged in domestic work, 43% were also engaged in working on the farm. The average weekly hours of child work across the three categories (farm work only, domestic work only and a combination of work on the farm and at home) is 25 hours per week. In terms of the proportion of children working across various activities, our numbers are consistent with those of the Ethiopian National Child Labor Survey of 2015[16] where 71% of children are engaged in domestic work.The information on school attendance, however, in our sample is slightly problematic. This is due to a surprisingly large number of missing observations compared to those in the child labor variables, but also because of the fact that the answer of approximately 10% of the respondents to the question of whether the child attended school during the reference period was “Not Applicable”. A close look at the data indicates that many of these answers are clustered around child ages of 7 and 13-15, which would normally indicate that while children in these marginal groups are not attending school their parents consider going to school not applicable. Our experience with primary data collection also indicates that due to a desire to hide school non-attendance parents would prefer to opt for the “Not Applicable” category than report not going to school outright. Although we base our empirical analysis by treating the “Not Applicable” responses to schooling information as missing observations, we also analyze the case where the “Not Applicable” responses are treated as zeros. This robustness check- available upon request- does not affect our conclusions.

[16] We thank an anonymous referee for pointing this out.

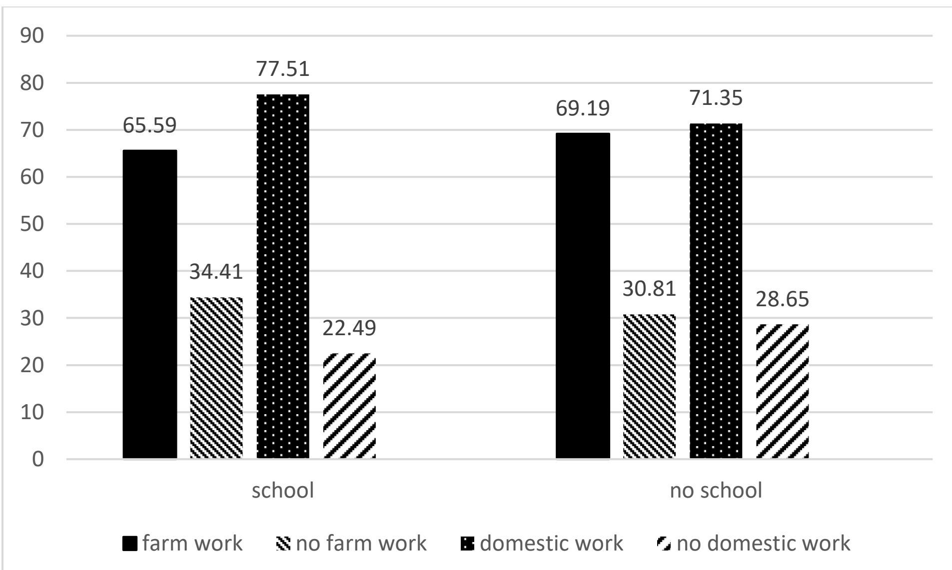
Table 3: Descriptive Statistics

	mean	sd	min	max	obs
Farm work (incidence)	.6371416	.4809274	0	1	2337
Domestic work (incidence)	.7663671	.4232318	0	1	2337
Combined work (incidence)	.4291827	.4950654	0	1	2337
Hours farm work	12.71801	13.51694	0	56	2337
Hours domestic work	12.74176	11.16356	0	56	2337
Total hours (farm, domestic and combination of farm and domestic work)	25.45978	13.50866	0	56	2337
School attendance (N/A excluded)	.9053708	.2927769	0	1	1955
School attendance (N/A included)	.8152925	.3881495	0	1	2171
Child age	11.11425	2.582085	7	15	2337
Girl	.4848096	.4998762	0	1	2337
Biological child	.8395379	.3671127	0	1	2337
Biological grandchild	.0979889	.2973632	0	1	2377
High risk taker	.4458708	.4971678	0	1	2377
Least patient	.6375695	.4808051	0	1	2377
Medium patient	.1583226	.3651214	0	1	2377
Female respondent	.198973	.3993132	0	1	2377
Respondent's education	.6063329	.4886671	0	1	2377
Respondent farmer	.8185708	.3854558	0	1	2377
Household proportion female less than 5 years	.0420898	.075226	0	.4	2377
Household proportion male less than 5 years	.0453435	.0783798	0	.4	2377
Household proportion female 5-15 years	.1914474	.1467052	0	.8	2377
Household proportion male 5-15 years	.1994205	.1428406	0	.6666667	2377
Household proportion female more than 60 years	.0245966	.0737808	0	.6666667	2377
Household proportion male more than 60 years	.0312521	.0685141	0	.5	2377
Household size	7.146341	2.314889	2	16	2377
Land size in hectares	2.369035	4.532624	.0003	125.406	2377
Livestock value	9176.177	11961.14	0	97210	2377

The rest of the statistics reported in Table 3 above indicate that around 45% of the respondents can be defined as risk takers, 64% of them fall in the least patient and 16% in the medium patience category. Only 20% of the respondents are female, 61% of them have attended at least some schooling during their lives; the majority, namely 82% are involved in farming as a primary occupation. The proportion of children in the 5-15 age group exceeds that of dependents in the less than 5 and more than 60 years' categories. The average household size is 7, land holdings are relatively small - on average 2 hectares (although there are large farms of up to 125 hectares) and the average livestock value is 9176 Birr.

Figure 3 highlights the involvement of school-going children in farm and domestic activities separately from those children who do not attend school at all. While close to 70% of the children who do not go to school are involved in farm work, this is true for 66% of the children attending school. The corresponding proportions for children who are involved in domestic activities are 71% and 77%[17]. Since the joint child labor-schooling decision might be influenced by the category of work that a child engages in, we analyze the household head's risk and time preferences on the joint child labor-schooling outcomes separately in Section 6.

Figure 3: Child labor-Schooling Outcomes by Work Category.



[17] The proportion of children combining schooling with work in rural Ethiopia is non-trivial. The Ethiopian National Child Labor Survey of 2015 reports 51% of children in the 5-17 age group being engaged in economic activities with 30% of those combining economic ectivities with schooling.

4. Empirical Approach and Estimation Issues

Following convention in the literature, we start by estimating the baseline model of the total number of weekly hours of child labor:

$$H^* = X\boldsymbol{\beta} + \boldsymbol{e} \qquad (10)$$

where H^* is weekly hours of work by a child i in household j, irrespective of the category of work (farm or domestic). Vector X includes the risk and time preference variables described in section 2 as well as various other child and household level control variables used in the literature on rural child labor supply (summarized in Table 3) while $\boldsymbol{e}$ is a normally distributed error term. Given the considerable variation in hours, hours of work provides a more useful measure of the intensity of child labor than participation alone. However, as Figure 3 highlights, each category of work might have different implications for child schooling, and may also well be gender specific with boys predominantly engaged in farm work while girls involved in domestic work. Therefore as a robustness check, we supplement our baseline hours of work estimate with a set of linear probability and logit estimates of the incidence of child labor (i.e., whether or not a child participates) in farm and domestic work.

A key econometric concern is the possibility that the link between adult risk and time preferences is driven by time invariant unobservables, such as innate ability or preferences that are common for the child and the adult. To address this issue, we opt for two different tests of potential omitted variable bias. First, we implement the Oster (2019) coefficient stability test. As a critical response to prior literature, the test is based on the premise that stability of the coefficient of interest after inclusion of observed controls does not necessarily reduce an omitted variable bias. Indeed, the bias arising from observed variables (for instance, in our case, variables that capture the level of poverty of a household), may be informative of a bias related to unobserved variables. Briefly, Oster's (2019) approach relies on estimating a controlled regression that includes all observed factors suggested by economic theory and an uncontrolled regression that includes only covariates that are not informative of selection on unobservables. There are two key parameters that specify the relationship between observables and unobservables, as well as the maximum amount of variation that can be explained by the model. A parameter δ defines the importance of unobservables relative to observables in influencing the key explanatory variable of interest. When δ=1 observables and unobservables are equally important and affect $\boldsymbol{\beta}$ in the same direction. The second important parameter, R_{max}, is the maximum $R - squared$ under the full model where all observables and unobservables are included. Both δ and R_{max} are unknown and are to be chosen given the specific context at hand. In practice, researchers explore the stability of coefficients by setting δ=1 and experimenting with R_{max}=1.3$\tilde{R}$ and R_{max}=2.2 $\tilde{R}$, where $\tilde{R}$ is the $R - squared$ based on the full specification, as upper limits on the potential amount of variation that could be explained by the model. We follow this routine.

For further reassurance of the absence of omitted variable bias and hence robustness of our baseline results we also implement the Double Lasso (DL) routine available in Stata 16 (Urminsky et. al., 2016). This is machine learning technique chooses appropriate control variables on the basis of a data mining process and comes up with unbiased estimates of the variables of interest after selecting from a pool of potential controls only those with the highest statistical validity. Table 6 reports the results from the Oster and DL tests.

5. Empirical Results

Table 4 highlights the marginal effects from the Tobit based hours of work estimation. Given that respondents report as child labor the supply of even 2 or 3 hours of work per week, we experiment with two versions of the estimates, one based on the full sample, and one restricting the sample to child labor supply to at least 21 hours per week. This latter cut-off requires an average supply of at least 3 hours of work per day and is thus more akin to actual provision of "labor" as opposed to occasional help on the farm or within the household. Column 2 reports the marginal effect of each variable evaluated at the mean, conditional on censoring for the sample as a whole, while Column 3 refers to the corresponding probability of being censored, which in keeping with Bhalotra (2003) and Bhalotra and Heady (2003) we interpret as the probability of participation. In Columns 4 and 5 we report the results for the sample restricted to at least 21 hours of child work per week.

The most important finding is that both participation and the hours of work, conditional on censoring, are a positive function of the level of risk aversion and a negative function of the level of patience of the adult respondent. Specifically, the probability of children working is reduced by 0.43 percentage points when the adult respondent is a high-risk taker as compared to a low-risk taker. The corresponding probability for the restricted sample is 3.335 percentage points. Furthermore, adult respondents with the least amount of patience increases the probability of child work by 0.5 percentage points (3.41 percentage points for the restricted sample) compared to the omitted category of adult respondents with the highest level of patience. Similarly, belonging to the high risk taker category reduces the hours of child labor by 0.974 compared to the case of adult respondents belonging to the low risk taker category (the corresponding effect for the restricted sample being 1.329)[18].

The results related to our control variables are consistent with expectations. Older children are both more likely to participate, and to supply higher number of work hours, while girls are both less likely to work and - conditional on working - supply fewer work hours than boys. This is consistent with evidence from the Ethiopian setting where land is inherited mostly by males (Slavchevska et. al., 2020)[19] while girls bring in a bride price to the household (Fafchamps and Quisumbing, 2005). Biological children of the respondent supply fewer hours of work. Higher level of education of the adult respondent reduces both the probability of child employment and the hours supplied, while the opposite is true for adult respondents whose primary occupation is farming. Finally, greater household size reduces both the probability of child labor and the number of hours supplied, while land size and the value of livestock do not influence child labor.

Next, we analyze the impact of adult risk and time preferences on the incidence of child labor supply for the two different child labor categories - farm labor and domestic labor as a robustness check of our baseline results. Incidence is captured by a participation dummy where child engagement in each of these work categories is assigned a value of 1 and 0 otherwise.Table 5 reports the estimates from a linear probability model and the marginal effects from a logit model

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[18] Note that we have dummy variables as controls (high and low risk taker; and least, medium, high patience). One category for risk and patience needs to be omitted to avoid multicollinearity. We thus include all but one dummy and interpret the coefficients for the included vis-a-vis the excluded one.

[19] Slavchevska et. al. (2020) provides an analysis of rights in Ethiopia where land is typically owned by the State and individual have land use rights. These rights can be transferred, specially in rural areas but there are restrictions on using land as collateral and land rentals. In 1997, Ethiopia started a land certification program which included both the husband and wife's names in the land use rights.

on the incidence of child labor for these three categories. Given the similarity of the results and the superiority of the logit model for the case of discrete dependent variables, we focus on the interpretation of the logit marginal effects.

These estimates based on participation confirm our baseline results in Table 4, and offer additional insights. Specifically, we find that children belonging to high-risk taker households have 3.94 percentage point lower probability of working on the farm and 3.88 percentage point lower probability of engaging in domestic work. While the marginal effects of the time preference variables are not significant in the case of domestic work, the marginal effect of 0.599 of the least patient variable is positive and significant at the 5% level in the farm labor case, highlighting a 5.99 percentage point greater probability of children to work on the farm if the adult respondent is very impatient.

The results with respect to the other controls show that boys are significantly more likely to work on the farm, while girls are significanlty more likely to be involved in domestic work activities. Interestingly, grandchildren are more likely to supply domestic work, plausibly on account of the fact that a vast majority of household work is care related. This is in line with the finding that greater proportion of young children (of less than 5 years of age) increases the probability of domestic work. Greater wealth in the form of larger plots of land and livestock holding decrease the probability of domestic work, even though these variables are insignificant for farm work. As expected, the probability of child labor on the farm goes up if farming is the primary occupation of the adult respondent. Household size negatively affects child involvement in domestic and joint (farm and domestic) activities but is insignificant for farm labor.

Table 6 highlights the results from our coefficient stability (Oster, 2019) and Double Lasso (DL) robustness checks. We report the unbiased beta parameter estimates for different choices of R*max* in the case of the Oster (2019) routine, and the corresponding DL counterparts. Our interest is in identifying if the beta parameter changes its sign across the different specifications. Reassuringly, the signs of the parameter are stable for all specifications related to farm work. In the case of domestic work, the parameter swaps sign in the DL estimate related to the least patient variable and the Oster ($R_{max} = 1.3R$) estimate of the medium patient variable. However, both of these variables are insignificant in our baseline regressions. In the case of hours of work, the beta estimate of the high-risk taker variable changes sign in the Oster case of $R_{max} = 2.2R$. Yet, $2.2R$ is an unreasonably high limit of the potential level of explained variation and the beta parameter swaps sign even in Oster's (2019) experimentation with $R - squared$ limits. The second parameter that swaps sign is the Double Lasso estimate of the middle patience variable, which as in the case of the domestic work estimates is always insignificant in our regressions. In sum, our robustness checks grant support to the unbiasedness of our key baseline results.

6. Mechanisms

Our central finding is that higher adult risk aversion and lower adult patience increases the probability of a child working. This result endures even with the disaggregation of child work into various categories (farm and domestic work), and a variety of robustness checks. The mechanism that drives the result is highlighted by our theory where investment in child education acts as insurance for an adult in old age, and low or uncertain future retuns to education induce relatively more risk averse adults to invest less in education and prefer child work in the current period. A relatively more patient adult, all else constant, discounts future income less and hence prefers education to child labor in the current period.

To test our theoretical prediction further, we estimate a multinomial logit of child labor supply and schooling, which takes the value of one if children work while attending school, a value of two when children work without going to school, a value of three when children only go to school but are not engaged in work activities and a value of four when children neither work nor go to school[20]. However, to ensure that the child labor-schooling trade-off is a meaningful decision for the household head, we use the threshold of at least 21 hours of work per week as in Table 4. Given that almost all children in our sample provide some hours of work on the farm or within the household, our focus here is on the level of child work which can start having a detrimental effect

[20] See for example Maitra and Ray (2002) for the joint child labor and schooling estimation techniques. Incidentally, one of the earliest papers to analyze the child labor-schooling outcome is Psacharopoulos (1997) for Bolivia and Venezuela where the educational attainment of working children is 2 years lower as compared to children who do not work. More recently, Tang, Zhao and Zhao (2020) exploit the compulsory education policy in China to show that free compulsory education only has an effect on reducing child labor for boys but not for girls.

on school attendance and performance[21]. The marginal effects of this model are presented in Table 7 for the full sample of children as well as for those engaged in farm and in domestic work separately. In all three cases, the marginal effect of the high-risk variable is negatively associated with the probability of working while attending school. The probability of children belonging to the households of high-risk takers to combine work and schooling is less than that of children belonging to the households of low-risk takers by 0.05 in the case of farm labor, 0.04 in the case of domestic labor, and the sample as a whole. By contrast, the marginal effects of the high-risk taker variable is of the same size but with the opposite sign in the multinomial logit category related to schooling with no child labor. This indicates that risk averse parents are more likely to combine schooling and child labor and less likely to involve children in only schooling. Finally, the marginal effect of the least patient variable is positively associated with the probability of child work on the farm and no schooling, and negatively associated with the probability of attending school and not working on the farm[22].

Finally, there are a couple of competing hypotheses that we need to address. First, is it possible that market imperfections as in Bhalotra and Heady (2003) and Bhalotra (2003), where the incidence of child labor is positively correlated with the size of land and negatively correlated with other assets (such as livestock) are influencing our results? Second, and as noted in the Introduction, could a positive association between wealth (proxied by land size or livestock value) and child labor supply be attributed to increasing relative risk aversion (IRRA)? The results presented in Tables 4 and 5 do not grant support to either hypotheses as land size and livestock are

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[21] Our choice of at least 21 hours of work per week is guided by the findings of Admassie and Bedi (2003) who uses the fifth round of the Ethiopia Rural Household Survey (1999/2000) to analyze the effect of hours worked by a child on school enrollment and their reading and writing ability. Admassie and Bedi finds that around 16-22 hours of work per week tends to adversely affect reading and writing ability while 21-31 hours of work per week adversely affects school attendance.

[22] Several studies have analyzed the determinants of schooling in Ethiopia by focusing on non-behavioral household and geographical characteristics. As examples, Admassie and Bedi (2003) finds that parental education has a strong positive effect on school attendance, as does the number of cattle owned by the household. Schaffner (2004) uses 3 Ethiopian datasets (Labor Force Survey, 1999; Demographic, Family and Heath Survey, 2000 and the Household Income and Consumption Expenditure Survey, 1999/2000) to find that child schooling is positively influenced by distance to school and literacy level of the household head while having more adult males and higher number of young dependents within the household negatively affects school enrollment (Ch. 6, pp 50). More recently, Mani, Hoddinott and Strauss (2013) uses the Ethiopia Rural Household Survey (1989-2004) to find that parental education levels have a significant positive effect on school enrollment.

routinely insignificant in our regressions after accounting for adult behavioral preferences and other controls. The livestock variable is only significant in the Tobit estimates for the sample as a whole. Yet the sign of the coefficient is positive and possibly indicative of a complementarity between livestock care and child work (Haile and Haile, 2012). As a further robustness check, we re-run the regressions for both the incidence of child labor on the farm as well as the hours supplied on the farm, but with the adult high-risk taker variable interacted with land size. The rationale is that in the context of imperfect or missing labor markets in rural areas, risk averse land owners whose land size is large enough to require additional manpower would be particularly inclined to engage family (including child) labor to reduce monitoring costs. The results, reported in Table 8, indicate that this is not the case: the interaction term between the adult risk preference variable and land size is not significant. This robustness check also eliminates increasing relative risk aversion (IRRA) as a possible driver of our results.

7. Conclusion

Child labor remains a pervasive phenomenon in developing economies. Rural areas of sub-Saharan Africa are characterized by the largest incidence and intensity of child labor and its consequence in terms of impaired childhood development, low educational attainment and fewer gainful employment opportunities as adults is well documented. While previous research has identified poverty and market imperfections as primary determinants of child labor with accompanying policy prescriptions that target households accordingly, no research has explored whether behavioral preferences of household heads (in terms of risk profiles and time preferences) are systematically correlated with either the existence of child labor or it's intensity.

We provide a link between the risk and time preferences of household heads and the child labor-education outcomes. Our conclusion that child labor is a result of adult risk aversion and impatience is an intuitive corollary to the orthogonal findings on education under the assumption that child labor is the alternative of schooling. Our results grant support to the theory that even though investment in a child's education provides old-age insurance for adults, high risk aversion to future uncertain returns to education act as an incentive to send children to work in the present period. Our results are interesting from a policy point of view. Although much of the academic literature and policy discourse assume that schooling and child labor are substitutable and hence assuring free schooling or cash transfers aimed at keeping children at school would potentially resolve the child labor problem, we feel instead that policies geared towards reducing the uncertainty associated with the returns to education (via labor markrt reforms such as policies that reduce job search costs and adult minimum wages) or the provision of old-age insurance (health or life insurance) which lessens the reliance on one's offspring's income in old age might be more appropriate interventions.

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Table 4: Marginal Effects of Tobit Estimates - Weekly Hours of Child Work

	Full sample		Restricted sample >=21 hrs per week	
VARIABLES	Conditional hours	Probability	Conditional hours	Probability
child age	0.940***	0.00413***	0.988***	0.0247***
	(0.0937)	(0.00041)	(0.111)	(0.00277)
Girl	-1.399**	-0.00618**	-1.824***	-0.0457***
	(0.549)	(0.00241)	(0.643)	(0.0161)
biological child	-2.017**	-0.00774*	-2.003*	-0.0467
	(0.996)	(0.00437)	(1.147)	(0.0287)
biological grandchild	1.512	0.00753	1.79	0.0481
	(1.234)	(0.00542)	(1.427)	(0.0357)
high risk taker	-0.974**	-0.00433**	-1.329**	-0.0335**
	(0.49)	(0.00215)	(0.576)	(0.0144)
least patient	1.270**	0.00579**	1.338*	0.0341*
	(0.619)	(0.00272)	(0.722)	(0.018)
medium patient	-0.196	-0.00087	-0.315	-0.00795
	(0.803)	(0.00353)	(0.944)	(0.0236)
female respondent	0.224	0.00097	0.474	0.0117
	(0.822)	(0.00361)	(0.964)	(0.0241)
respondent's education	-1.334**	-0.00570**	-1.190*	-0.0294*
	(0.543)	(0.00238)	(0.637)	(0.0159)
respondent farmer	1.515**	0.00736**	1.733**	0.0458**
	(0.731)	(0.00321)	(0.861)	(0.0215)
proportion female less than 5 years	9.112***	0.0400***	9.843***	0.246***
	(3.224)	(0.0141)	(3.777)	(0.0944)
proportion male less than 5 years	1.418	0.00622	2.512	0.0628
	(3.164)	(0.0139)	(3.723)	(0.0931)
proportion female 5-15 years	3.132	0.0137	3.745	0.0936
	(2.075)	(0.00911)	(2.419)	(0.0605)
proportion male 5-15 years	1.71	0.00751	1.391	0.0348
	(2.093)	(0.00919)	(2.445)	(0.0611)
proportion female more than 60 years	5.792	0.0254	6.365	0.159
	(3.614)	(0.0159)	(4.176)	(0.104)
proportion male more than 60 years	1.488	0.00653	3.826	0.0956
	(3.889)	(0.0171)	(4.511)	(0.113)
household size	-0.346***	-0.00152***	-0.486***	-0.0121***
	(0.122)	(0.00054)	(0.143)	(0.00358)
land size hectares	-0.0311	-0.00014	0.0155	0.000387
	(0.0563)	(0.00025)	(0.0647)	(0.00162)
livestock value	0.717***	0.00315***	0.472	0.0118
	(0.263)	(0.00115)	(0.303)	(0.00756)
Constant	12.92***	0.0567***	-1.012	-0.0253
	(2.389)	(0.0105)	(2.81)	(0.0702)
Log likelihood	-9033.8949		-7611.9081	
Observations	2,337	2,337	2,337	2,337

Note: The figures in brackets are standard errors, ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. Marginal effects are evaluated at the sample mean. "Participation probabilities" are the marginal effects of the probability of being censored, while "Hours conditional on truncation" refer to the marginal effects conditonal on censoring. The results are robust to controlling for Peasant Association fixed effects; where Peasant Associations are locational variables close to the village level. The standard errors are robust to clustering at the household level.

Table 5: Child Labor Incidence by Work Type

	Farm labor		Domestic labor	
VARIABLES	LPM	logit margins	LPM	logit margins
child age	0.0102***	0.0103***	0.0138***	0.0158***
	(0.00373)	(0.00363)	(0.00309)	(0.00294)
Girl	-0.394***	-0.364***	0.323***	0.341***
	(0.0217)	(0.0179)	(0.0196)	(0.0196)
biological child	-0.0282	-0.0308	0.0540	0.0509
	(0.0362)	(0.0376)	(0.0351)	(0.0331)
biological grandchild	-0.0179	-0.0223	0.0783*	0.0777*
	(0.0474)	(0.0472)	(0.0434)	(0.0418)
high risk taker	-0.0413*	-0.0394*	-0.0389**	-0.0355**
	(0.0233)	(0.0228)	(0.0182)	(0.0178)
least patient	0.0614**	0.0599**	0.00311	0.00375
	(0.0289)	(0.0279)	(0.0210)	(0.0202)
medium patient	0.0483	0.0486	-0.0103	-0.0107
	(0.0361)	(0.0352)	(0.0274)	(0.0259)
female respondent	0.0186	0.0172	0.0143	0.0255
	(0.0399)	(0.0385)	(0.0291)	(0.0313)
respondent's education	-0.0286	-0.0263	0.0466**	0.0562***
	(0.0249)	(0.0246)	(0.0193)	(0.0189)
respondent farmer	0.0786*	0.0772*	-0.0332	-0.0340
	(0.0422)	(0.0397)	(0.0262)	(0.0301)
proportion female less than 5 years	0.0484	0.0438	0.267**	0.306***
	(0.154)	(0.153)	(0.109)	(0.112)
proportion male less than 5 years	-0.315**	-0.313**	0.256**	0.270**
	(0.143)	(0.140)	(0.119)	(0.121)
proportion female 5-15 years	-0.0153	-0.0157	-0.0258	-0.0547
	(0.0947)	(0.0939)	(0.0720)	(0.0738)
proportion male 5-15 years	-0.231**	-0.239**	0.175**	0.151**
	(0.0978)	(0.0992)	(0.0728)	(0.0733)
proportion female more than 60	-0.425***	-0.403***	0.0195	0.0356
	(0.150)	(0.146)	(0.118)	(0.129)
proportion male more than 60	-0.108	-0.113	0.00331	0.0164
	(0.167)	(0.164)	(0.138)	(0.135)
household size	0.000537	0.000592	-0.0155***	-0.0142***
	(0.00599)	(0.00587)	(0.00420)	(0.00406)
land size hectares	-0.00105	-0.00111	-0.00211**	-0.00139**
	(0.00153)	(0.00129)	(0.000821)	(0.000547)
livestock value	0.0160	0.0164	-0.0159*	-0.0158**
	(0.0124)	(0.0137)	(0.00936)	(0.00769)
Constant	0.839***		0.112	
	(0.103)		(0.0872)	
R-squared	0.217		0.295	
Observations	2,337	2,337	2,337	2,337

Note: The figures in brackets are standard errors, ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The results are robust to controlling for Peasant Association fixed effects; where Peasant Associations are locational variables close to the village level. The standard errors are robust to clustering at the household level.

Table 6: Unbiased Beta Coefficients, Oster and Double Lasso

	Oster, Rmax=1.3R	Oster, Rmax=2.2R	Double Lasso
		Hours of work	
high risk taker	-0.87414	**0.28753**	-1.174969
least patient	1.73013	6.57657	1.175055
medium patient	0.41361	7.03429	**-0.8167246**
		Farm labor incidence	
high risk taker	-0.03507	-0.01286	-0.0298204
least patient	0.07043	0.22060	0.0731652
medium patient	0.08242	0.42176	0.0467827
		Domestic labor incidence	
high risk taker	-0.04378	-0.06103	-0.0541302
least patient	0.00732	0.07790	**-0.0271136**
medium patient	**-0.00382**	0.07853	-0.0496781

Table 7: Marginal Effects from the Multinomial Logit Model on Child Labor and Schooling

	CL-ED	CL-NoEd	NoCL-Ed	NoCL-NoEd
			Total work	
high risk taker	-0.0439**	0.0002	0.0428**	0.0009
	(0.0215)	(0.0121)	(0.0197)	(0.0067)
least patient	0.0343**	0.0343	-0.0458*	-0.0025
	(0.0164)	(0.0164)	(0.0261)	(0.0082)
medium patient	-0.0405	0.0168	0.0271	-0.0034
	(0.0358)	(0.0211)	(0.0325)	(0.0109)
			Farm labor	
high risk taker	-0.0515**	0.0051	0.0516***	-0.0052
	(0.0214)	(0.0113)	(0.0197)	(0.0008)
least patient	0.0261	0.0493***	-0.0624**	-0.0131
	(0.0273)	(0.0167)	(0.0244)	(0.0091)
medium patient	0.017	0.0342*	-0.0338	-0.0173
	(0.0356)	(0.0205)	(0.0320)	(0.0131)
			Domestic labor	
high risk taker	-0.0422**	-0.0151	0.0424***	0.0149
	(0.0191)	(0.0117)	(0.0162)	(0.0078)
least patient	-0.0148	0.0167	-0.0141	0.0121
	(0.0243)	(0.0150)	(0.0206)	(0.0104)
medium patient	0.0067	-0.0133	-0.0131	0.0196
	(0.0319)	(0.0209)	(0.0265)	(0.0121)

Note: The figures in brackets are standard errors, ***, **, * represents significance at the 1%, 5% and 10% level, respectively. The results meet the IIA condition. The regression analysis includes the full set of control variables highlighted in Tables 4 and 5.

Table 8: Verification of the Role of Market Imperfections: Farm Hours of Child Work

VARIABLES	Conditional hours	Probability
child age	0.138**	0.00621**
	(0.0702)	(0.00316)
girl	-9.430***	-0.409***
	(0.421)	(0.0189)
biological child	-1.838**	-0.0757**
	(0.737)	(0.0331)
biological grandchild	-1.660*	-0.0818**
	(0.919)	(0.0413)
high risk taker	-0.689	-0.0311
	(0.497)	(0.0223)
least patient	1.151**	0.0528**
	(0.467)	(0.021)
medium patient	1.054*	0.0450*
	(0.606)	(0.0272)
female respondent	0.531	0.0234
	(0.618)	(0.0278)
respondent's education	-1.080***	-0.0477***
	(0.407)	(0.0183)
respondent farmer	1.669***	0.0807***
	(0.555)	(0.0249)
household proportion females less than 5 years	1.594	0.0716
	(2.405)	(0.108)
household proportion males less than 5 years	-5.644**	-0.254**
	(2.383)	(0.107)
household proportion of females 5-15 years	0.00303	0.000136
	(1.567)	(0.0704)
household proportion of males 5-15 years	-4.727***	-0.212***
	(1.565)	(0.0703)
household proportion of females more than 60	-4.341	-0.195
	(2.826)	(0.127)
household proportion of males more than 60	1.073	0.0482
	(2.898)	(0.13)
household size	0.00476	0.000214
	(0.0924)	(0.00415)
land size hectares	-0.0164	-0.000737
	(0.0412)	(0.00185)
livestock value	0.405**	0.0182**
	(0.204)	(0.00915)
highrisk*landsize	0.0606	0.00272
	(0.166)	(0.00744)
Constant	10.78***	0.484***
	(1.786)	(0.0802)
Log-likelihood	-6841.6149	
Observations	2,337	2,337