The Consequences of Child Labor: Evidence from Longitudinal Data in Rural Tanzania*

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Abstract

This paper exploits a unique longitudinal data set from Tanzania to examine the consequences of child labor on education, employment choices, and marital status over a 10-year horizon. We use crop and rainfall shocks as instrumental variables for child labor. For boys, we find that a one standard deviation (5.7 hour) increase in child labor leads 10 years later to a loss of approximately one year of schooling and to a substantial increase in the likelihood of farming and of marrying at a younger age. Strikingly, we find no significant effects on education for girls, but do find a significant increase in the likelihood of marrying young and some evidence of reduced labor productivity. We also find that crop shocks lead to an increase in agricultural work for boys and instead lead to an increase in chore hours for girls. Our results are consistent with education being a lower priority for girls or with chores causing less disruption for education than agricultural work. The increased chore hours could also account for our results on marriage and labor productivity for girls.

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I. Introduction

This paper exploits a unique longitudinal data set from Tanzania to examine the impact of child labor on education, employment choices, and marital status over a 10-year horizon. The question is important for many reasons. The assumption that work is harmful to children's development underpins both the theoretical literature and the policy debate on child labor. For example, from the policy perspective, there is a general perception that the worldwide returns to eliminating child labor are substantial (see International Labour Organization [ILO], 2003). However, the evidence that rigorously quantifies the consequences of child labor is limited.

Theoretically, it is unclear whether and to what extent child labor is harmful. In rural settings in developing countries (which is where more than 70 percent of the world's child labor occurs; ILO, 2002), child labor tends to be a moderate-intensity activity, while at the same time schooling is part time and intermittent. Child labor may also provide the child with work experience that subsequently could be rewarded in the labor market. The overall effect is ambiguous.

Empirically, although there is a large and growing body of evidence that child labor is harmful (reviewed in Section 2), the existing literature has many limitations, some of which we seek to overcome in this paper. First, most papers focus exclusively on schooling as an outcome. Although schooling is central, it is also important to consider other outcomes, in particular outcomes that allow us to measure possible effects of child labor on economic activity (in this paper we look at occupation, crop choices, and labor productivity). Second, most papers in this literature examine correlations, rather than causal relationships. There are many reasons in the context of child labor that correlation need not imply causation. Both between and within households there is selection along observable (education, wealth, occupation, children's age,

and gender) and unobservable (social networks, concern for children, child ability) dimensions. In this paper we use an instrumental variables strategy which we describe below. Third, almost all papers in this literature are confined to looking at the contemporaneous or short-horizon effect of child labor. There is no direct evidence on the longer-run impact of child labor, a limitation we remedy in this paper with a data set that spans 13 years.

Our strategy is to examine the long-run consequences of child labor using the Kagera Health and Development Survey in Tanzania, which is comprised of five waves, spanning 13 years. We study the relationship between child labor (measured by hours spent on household chores and in economic activity) in early waves (1991-1994) and outcomes (such as education, whether or not the individual is farming, choice of cash versus subsistence crop, marital status, and labor productivity) in the final wave (2004). We instrument for child labor using crop and rainfall shocks. In previous work (Beegle, Dehejia, and Gatti, 2006), we have shown that crop shocks are predictive of child labor; we argue below that they, along with rainfall shocks, are plausible instrumental variables (i.e., that they satisfy conditional exogeneity and the exclusion restriction).

We find that child labor is causally associated with reduced educational attainment (as measured by years of schooling and by an indicator for completion of primary school). Interestingly, this result appears to be entirely driven by the sample of boys, for whom a one standard deviation (5.7 hour) increase in child labor implies nearly one year less of schooling. Boys who worked when young are more likely to be farming (as opposed to earning a wage). We do not find that child labor is associated with discernible differences in the choice of crop (cash versus subsistence) or subsequent migration. For girls, the only robustly significant effect of

child labor is an increased probability of being married 10 to 13 years later, although in some specifications we also find a negative effect on the marginal productivity of labor.

The paper is organized as follows. Section II briefly reviews the existing literature. Section III introduces the data, and Section IV describes the empirical methodology and discusses in detail the plausibility of our instrumental variables approach. Results are presented in Section V, and Section VI discusses refinements and extensions. Section VII concludes.

II. Literature Review

There is a rapidly-expanding literature on child labor. In this section we briefly review key findings that put our own work in perspective. Edmonds (2007) offers a more detailed survey.

There is a large literature that has established a negative correlation between child labor and school attainment. For example, Patrinos and Psacharopoulos (1995) show that factors that predict an increase in child labor also predict reduced attendance and an increased chance of grade repetition; Patrinos and Psacharopoulos (1997) further show that child work is a significant negative predictor of age-grade distortion. A number of papers have used test scores as an outcome. These include Akabayashi and Psacharopoulos (1999), who show that children's reading competence (as assessed by their parents) decreases with child labor hours, and Heady (2003), who finds a negative relationship between child labor and objective measures of reading and mathematics ability in Ghana.

A more recent literature tries to estimate causal effects rather than correlations. These papers use a number of strategies. Boozer and Suri (2001) use regional variation in rainfall as a source of exogenous variation in child labor, and find that a one hour increase in child labor

leads to a 0.38 hour decrease in contemporaneous schooling. Cavalieri (2002) uses propensity score matching and finds that child labor is associated with a 10 percent reduction in the probability of being promoted to the next grade.

Papers using an instrumental variables strategy include Ray and Lancaster (2003), Beegle, Dehejia, and Gatti (2005), and Bezerra, Kassouf, and Arends-Kuenning (2007).[1] Each of these papers has strengths and weaknesses. Ray and Lancaster have micro data from seven countries, but their instruments (household measures of income and assets, and water, telephone, and electricity infrastructure) are unlikely to satisfy the exclusion restriction.[2] Beegle, Dehejia, and Gatti (2005) use community rice prices and crop shocks as instruments for child labor in Vietnam.[3] They estimate that child labor reduces the probability of being in school by 30 percent and educational attainment by 6 percent, but are limited to looking at outcomes over a 5-year horizon. Bezerra, Kassouf, and Arends-Kuenning (2007) use city population, state-level schooling, and literacy rates to instrument for child labor in Brazil. They find that working seven hours or more per day results in a 10 percent decrease in test scores relative to students who do not work. However, their instruments are likely to be correlated to city and state unobservables, and are unlikely to satisfy the exclusion restriction. Finally, Ravallion and Wodon (2000) use between-village variation induced by a food-for-school program in Bangladesh; they find that the program led to a significant increase in schooling, but only one eighth to one quarter of the increase in schooling hours is explained by decreased child labor.

[1] Krutikova (2006) uses the same data as this paper and focuses on educational attainment.
[2] For instance, they find that in Belize the initial hour of child labor leads to a reduction in years of schooling by 2.6 years. Note that in some cases they find the marginal impact of child labor to be positive. In particular, for Sri Lanka, the impact is positive for all school outcomes.
[3] Beegle, Dehejia, and Gatti (2005) also examine health outcomes for children, as do O'Donnell, Rosati and Van Doorslaer (2005), using the same data set.

The literature examining the link between child labor and subsequent labor market outcomes is much more limited. Indeed, the only papers we are aware of are Beegle, Dehejia, and Gatti (2005) and Emerson and Souza (2006). Beegle, Dehejia, and Gatti (2005) find that child labor is associated with a significant increase in wages 5 years later; the wage increase is sufficiently large to offset the cost of displaced education. Emerson and Souza (2006) instrument for child labor and child schooling using the number of schools per child in the state, the number of teachers per school, and GDP per capita at age 12. They find that, even controlling for completed schooling, child labor has a negative effect on adult earnings. The limitation of this paper is that child labor is measured retrospectively (in adulthood) and only for the sample of adults who are working for a wage. In contrast with these papers, the present paper observes child labor as it occurs and is able to follow individuals over a 10-year horizon.

III. Data description

III.1 Data set

The Kagera Region of Tanzania is located on the western shore of Lake Victoria, bordering Uganda to the north and Rwanda and Burundi to the west. The population (1.3 million in 1988, about 2 million in 2004) is overwhelmingly rural and primarily engaged in producing bananas and coffee in the north and rain-fed annual crops (maize, sorghum, cotton) in the south. This study uses baseline data from the Kagera Health and Development Survey (KHDS), a longitudinal socioeconomic survey conducted from September 1991 to January 1994 covering the entire Kagera region (World Bank, 2004). Because adult mortality of the working age population (15-50) is a relatively rare event and HIV/AIDS was unevenly distributed in Kagera, the KHDS household sample was stratified. In order to capture a higher percentage of

households with a death while retaining a control group of households without a death, stratification was based on agro-climatic features of the region, levels of adult mortality from the 1988 Census (including both high and low mortality areas), and household-level indicators thought to be predictive of elevated adult illness or mortality.

In 2004, another round of data collection was completed (Beegle, De Weerdt, and Dercon, 2006a). The goal of the KHDS 2004 was to re-interview the sample of 6,210 respondents from the 1991-1994 survey; this excludes 169 individuals who died over the course of the baseline rounds. In addition to the household survey, the KHDS 2004 included additional community-level surveys consistent with those carried out in the 1991-1994 rounds. A community questionnaire was administered to collect data on the physical, economic and social infrastructure of the baseline communities, as well as shocks experienced at the community level. Over the course of 10-13 years, it was anticipated that a substantial number of individuals would have migrated from the dwelling occupied in 1991-1994. Considerable effort was made to track surviving respondents to their current location, be it in the same village, a nearby village, within the region, or even outside the region.

Because of the long time frame of the KHDS panel, we are able to study behaviors of children in conjunction with outcomes for these children as young adults. Among children ages 7-15 studied in Beegle, Dehejia, and Gatti (2006), 75% were re-interviewed in 2004, 21% were not located, and 4% were deceased. Among the children we study here (for details on the sample restriction see Section III), 76% were re-interviewed in 2004. Of these, 18% had moved far from their original village but still resided in Kagera, 11% resided outside Kagera but in Tanzania, and 2% were residing in Uganda. These children were, on average, 11 years old in their last interview from the baseline rounds. By 2004, they were almost 23 years old (Table 1).

III.2 Descriptive statistics

Our definition of child labor is the total hours spent working in economic activities and chores in the previous week (including fetching water and firewood, preparing meals, and cleaning the house). Economic activities for children consist predominately of farming, including tending crops in the field, processing crops, and tending livestock. We include chores as well as economic activities because the concept of child labor typically (e.g., in the ILO standard) encompasses both,[4] although we will distinguish between the two to explain differences in our results for boys and girls. Children in the sample work on average 17 hours per week, of which 10 are spent on chores (Table 1). Girls spend on average 2.5 hours more than boys working on household chores; this difference is more pronounced among older girls. More than 90% of children have worked at least one hour in one of the baseline waves.

We use two instrumental variables: household crop shocks and rainfall shocks. Household crop shocks are measured as the proportion of crop accidentally lost to pests and fire during the baseline interview period. Rainfall was measured at 21 weather stations from 1980 onward. For each household, we use rainfall data from the nearest weather station. We construct the rainfall shock as the deviation of the total rainfall in the short and long rainy seasons preceding the interview from its 25-year average, scaled by its standard deviation. Table 1 shows that the average proportion of crop loss is 0.34. The mean of the rainfall shock is -0.11 (i.e., one

[4]It should also be mentioned that the concept of child labor does not necessarily refer to simply any work done by a child, but, rather, work that stunts or limits the child's development or puts the child at risk. However, in survey data it is difficult to isolate the portion of time spent working on the farm that qualifies under this nuanced definition.

tenth of a standard deviation less rain than the weather-station specific norm).[5] We discuss the plausibility of these instruments in Section IV.2 below.

Our education outcome variables are years of schooling and an indicator variable for having completed seven or more years of education (primary level). Individuals in the sample have an average of 6.4 years of schooling and 78 percent have completed primary school. We measure labor market outcomes with a range of variables, including whether the individual earns a salary or is farming and among those farming whether the individual is growing cash crops. As the economy in the Kagera region is based mainly on extensive farming, whether the individual earns a salary or is involved in cash cropping (mainly tobacco and coffee, rather than subsistence farming) are important indicators of success. We also examine the probability of migrating from the village[6] and the (imputed) marginal productivity of labor in agriculture.[7] The literature has suggested that plot-specific experience could be an important element of the rural economy (Rosenzweig and Wolpin, 1985). It is possible that child labor contributes to plot-specific experience, in which case we would see child labor associated with an increased likelihood of farming, lower individual mobility, or higher labor productivity.

Finally, we explore whether child labor significantly affects marital status. This is particularly interesting for our sample of girls, who tend to work more hours than boys, especially on household chores.[8] Since marriage is universal in Tanzania, we are examining the influence of child labor on the likelihood of earlier marriage. Age at marriage has been shown to

[5] By construction, the rainfall deviation variable is mean zero and has a standard deviation of one over the entire sample period, though not necessarily within sub-periods.

[6] While, in wave 5, 70 percent of re-interviewed individuals in the sample were still living in the same or in neighboring villages, mobility is associated with significantly higher income gains for panel respondents (Beegle, De Weerdt, and Dercon, 2006b).

[7] The marginal productivity of labor is imputed by estimating an agricultural production function. The value of total agricultural output is regressed on all inputs – including labor and implements – that are used in production. The procedure is based on Jacoby (1993).

[8] For example, girls between 10 and 15 work 22 hours per week (15 of which are spent on household chores), as opposed to 18 hours for boys (11 of which are spent on household chores).

be associated with worse outcomes for women and their children, including increased health risks as well as potentially "worse" marriage matches.[9]

IV. Empirical methodology

IV.1 Specification

We are interested in the relationship between outcomes in wave 5 (including education, occupation, and marital status) and the level of child labor intensity (which we measure through mean child labor hours in waves 1 to 4). An OLS regression of the form

$$Y_{i,t} = \alpha + \beta T_{i,t-10} + \gamma X_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ are outcomes in wave 5, $T_{i,t-10}$ is mean child labor hours in waves 1 to 4, and $X_{i,t}$ are household and community-level controls, is most probably not suitable for estimating a causal relationship. The principal concern is omitted variable bias. The child labor decision is likely to be correlated with both household- and child-level covariates, not all of which will be observable to the researcher. For example, though we can control for parents' education we cannot control for their discount rates. At the child level, we have few covariates other than age and sex, and thus, for example, cannot control for ability. Reverse causality is less of a concern because the outcome is measured 10 years after child labor intensity.

We address concerns with the OLS specification using an instrumental variables strategy. Our instruments, $S_{i,t-10}$, are indicators of household agricultural shocks and rainfall shocks in waves 1 to 4. Thus our basic specification is a two-stage least squares procedure of the form:

$$T_{i,t} = a + bS_{i,t} + cX_{i,t} + v_{i,t} \tag{2}$$

[9] Younger mothers are more likely to suffer from micronutrient deficiencies and be unaware of the health risks associated with pregnancy; they are also more likely to have children soon after marriage with increased risk of maternal and infant mortality (World Bank, 2007). Younger ages at marriage may result in curtailed education for girls, although it is difficult to ascertain the causality. In any case, a younger bride may be less able to assert power and authority in her marriage especially given that women marry men who are on average several years older.

$$Y_{i,t} = \alpha + \beta \hat{T}_{i,t-10} + \gamma X_{i,t} + \varepsilon_{i,i}\,. \tag{3}$$

In practice, we also include interactions of one of the instruments (crop shocks) with a range of baseline characteristics (including age, sex, and land per capita) to increase predictive power in the first stage.

We impose several restrictions on the sample we examine. Following our previous work, we consider children between the ages of 7 and 15 in the baseline survey. Note that the prevalence of work among younger children is low. Likewise, by most definitions, working at age 16 and above would not be viewed as a particularly serious form of child labor. We also have information on whether children have ever been to school by wave 4. Tabulation of this variable shows that only 32% of 7-8 year olds had attended school at some point in time, which is consistent with the widespread tendency to delay enrollment, while among children age 13 and above only 12% had never been to school. It is unlikely that these older children who have not yet enrolled will enroll in the future. At the same time, the data suggest that, in response to a shock, households are more likely to employ the labor of the older, more productive children. Because of this, if we include these children in our sample, we would be likely to find a strong negative correlation between years of schooling and child labor. As a result, our sample includes all 7-15 year olds who were in school at the relevant wave and those children who had not yet entered school but were still young enough to have a chance to enroll (7-9 year olds).

IV.2 First-stage results and the plausibility of the instruments

In this section, we discuss whether crop and rainfall shocks plausibly satisfy the requirements for a valid instrumental variable.

Relevance

Both crop shocks and rainfall shocks affect the agricultural production function and as such could have an effect on the use of child labor. Crop shocks reflect occasions of agricultural stress or crisis, which are moments when the incremental value of child labor may be particularly high. Rainfall shocks are somewhat more ambiguous. Plentiful rainfall could be a positive shock to productivity, and, depending on the agricultural production function, could increase the marginal productivity of child labor. At the same time, extreme outliers of the rainfall deviation variable – essentially floods – are also possible, and their impact on the use of child labor is less clear. As it turns out, we do not observe any floods in the first four waves of the survey.

Our previous work and the estimates presented here confirm that crop shocks are significant predictors of child labor. Table 2 reports estimates from a first-stage regression, where total child labor hours (column (1)) are regressed on an indicator of crop shocks (and crop shocks interacted with age, land per capita, a female dummy, and age × female), rainfall shocks, and other regressors (such as region, parental education, log per capita expenditure, and household size). Column (2) presents the same specification for one of the two components of total work hours, hours spent in chores; results for the second component of total hours, hours spent in income-generating work, are not presented, but are available upon request.

The direct effect of a crop shock is a 3.8 hour increase in work and a 4.6 hour increase in chore hours (with the latter effect significant at the 5 per cent level). Notably the age interaction is negative for boys and positive for girls for both total work hours and chores: the incremental work in response to a shock for a 14 year old boy is almost the same as for a 7 year old boy (a difference of 0.3 hours per week), whereas among girls the older girl would work 4 hours more in response to a shock than the younger girl. The shock-land interaction is negative (albeit

insignificant), implying that the mean level of land holding negates one third of the increased work hours in response to a shock. The crop shock terms are jointly significant at the one percent level (with an F-statistic of 9). The rainfall shock has a positive and marginally significant effect (at the 11 percent level), suggesting that a typical high-rain season is associated with a quarter hour increase in child labor.

When we split work hours into economic hours (working outside the home in income generating activities) and chore hours and by boys and girls, we uncover some interesting differences. The direct effect of a crop shock on time spent on chores is negative for girls and positive for boys (although neither coefficient is statistically significant), but as can be seen in Table 2, the age-shock interaction is much larger for girls than boys; the interaction for girls is statistically significant at the one per cent level and statistically significantly greater than the point estimate for boys. At a younger age, chore hours increase by a similar amount for boys and girls in response to a shock, but for older girls the increase in chore hours in response to a shock is greater than for boys. For example, in response to a shock a 14-year-old girl will work 4 additional chore hours per week compared to a 7 year old, whereas for boys this differential is negligible. The pattern of variation in economic hours worked among girls is similar to that in chore hours, with a negative direct effect and a positive age-shock interaction. However, the magnitudes of the coefficients imply that for younger girls work decreases in response to a shock, albeit minimally, and for older girls the net effect is close to zero. Instead for boys, the increase in work hours is approximately 3.5 hours per week for a 7 year old and 5.5 hours per week for a 15 year old. The rainfall shock variable has a positive and weakly statistically significant effect on economic hours for girls and chore hours for boys.

Overall, this suggests that the incremental effect of the shock is to increase total work hours for both boys and girls, and to shift girls' labor hours from economic activities to chores, while among boys increasing economic activities to a greater degree than chores.

Exogeneity

Table 3 examines the plausibility of the exogeneity requirement for our instruments. Columns (1) to (3) regress crop shocks on lagged crop shocks and household characteristics; the regressions are at the household level. Column (1) shows that the occurrence of crop shocks is uncorrelated with most household characteristics, including household size, fathers' education and mothers' primary education. Crop shocks do appear to be negatively correlated with mothers' secondary education. It is worth noting less than 2% of the children in the sample have mothers with more than a primary education. Nonetheless, in our second stage specifications we include parental education as controls. Columns (2) and (3) show that the occurrence of crop shocks is uncorrelated with the occurrence of shocks in the previous two survey rounds. Columns (3) to (6) present analogous results for the rainfall shocks (these regressions are run at the village level). Rainfall shocks are also uncorrelated with characteristics of the child's household, but do appear to be correlated with rainfall in the previous survey wave (column (4)). In column (6) we see that the correlation in rainfall persists only for one year; rainfall lagged two years or more does not significantly predict rainfall in the survey year.

Overall, these results suggest that crop and rainfall shocks are plausibly uncorrelated with respect to household characteristics and over time. The one exception to this – mothers with 7 or more years of education – can be readily included as a control in the second stage.

The Exclusion Restriction

The remaining concern is whether the instruments satisfy the exclusion restriction, i.e. that they affect education and labor outcomes only through child labor. The relevance of this concern is supported by an influential strand of literature suggesting that transitory shocks can have long term consequences for households (see, for example, Ravallion and Lokshin, 2005). We investigate this concern in a number of ways. First, we examine the reduced form effect of agricultural and rainfall shocks in waves 1 to 4 on a range of outcomes 10 to 13 years later.[10] In particular, we regress wave 5 measures of household wealth, including values of physical and business assets, durables, farm equipment, land, and occupied dwellings on the average level of crop and rainfall shocks in waves 1 to 4. The effects are uniformly insignificant (Table 4). These results suggest, albeit indirectly, that given initial conditions, shocks in waves 1 to 4 did not have permanent effects on wealth variables in wave 5. In other words, they support the hypothesis that while shocks account for significant variation in child labor, their effects on other variables are likely to be short term.

Second, we exploit cross-sectional variation in the size of shocks to test whether our second stage results are driven only by large shocks or whether we obtain similar results for smaller shocks. Smaller shocks are a priori less likely to have long-lasting impacts on households, except through their impact on contemporaneous variables (child labor). We present these results below (in Section VI.3, along with other robustness checks).

Finally, we use the adults in our data as a comparison group for children. In particular, using the same specification that we use for children, we test whether labor hours for adults (those aged 20 and older) in waves 1 to 4 have a significant impact on outcomes in wave 5 when

[10] This could be extended by verifying that shocks are not correlated with such causes of attrition in the sample as mortality and destitution; this is work in progress.

instrumented with agricultural shocks. Adults do not, by definition, participate in child labor, which would imply two possible interpretations for any effect that we find: (1) that the instruments affect the outcomes directly, through some channel other than child labor (i.e., a violation of the exclusion restriction) or (2) that the instruments also have an impact on adult labor which in turn affects outcomes. We present and discuss these results in Section VI.2 below.

V. Results

V.1 Baseline OLS and reduced-form specifications

Prior to discussing our instrumental variables results, we first present the results of OLS and reduced-form specifications.

Table 5 presents results from an OLS regression of our outcomes as measured in wave 5 on average child labor over waves 1 to 4. Although the results are not statistically significant and are also likely to be biased, they are useful baseline estimates for comparison to our instrumental variables results. Child labor is associated with reduced schooling, which is measured by number of years of schooling attained and the probability of completing primary education. The negative association also holds for the probability of staying in or near the village (i.e., staying in the same village in wave 5 as in the last round of the baseline) and the probability of being a wageworker in the last 12 months. The results further suggest that child labor is positively correlated with the probability of being a farmer in the last 12 months, growing cash crops, being married, and labor productivity. Splitting the sample by gender shows that among girls child labor is associated with a statistically significant increase in the probability of marriage (which, given the sample characteristics, typically implies marrying at a younger age). However, because of the potential

sources of bias in this specification, as discussed in Section IV.1, we do not interpret these coefficients causally.

Table 6 presents reduced-form results of regressing our outcomes on the two instrumental variables. Because the two instruments are reasonably closely correlated, we present results for each reduced-form result separately[11]. The first panel of the table shows that an agricultural shock has a negative and statistically significant impact on education, measured by completed years of schooling and by an indicator for completing primary school. The magnitude of this effect is such that a shock in waves 1 to 4 leads to a one percent loss in education. Agricultural shocks do not appear to have any significant reduced-form effects on the remaining outcomes.

The rainfall shock has a negative and statistically significant impact on completed schooling; a one standard deviation increase in rainfall is associated with an 8.6 percent reduction in completed education. Further, rainfall has a significant impact on the probability of marriage. A one standard deviation rainfall shock leads to a 10 percent increase in the probability of marriage. As discussed below, these results are consistent with our IV estimates.

V.2 Instrumental variables estimation

We now discuss our instrumental variables estimates of the impact of child labor hours on the outcomes of interest. In the first stage, labor hours are predicted from a regression of child labor hours on shocks and their interactions (Table 2 and equation (3) above).[12]

[11] When both are included simultaneously, results are similar but standard errors are larger, consistent with multicolinearity

[12] Note that as we have on average 2.3 children in the relevant age range per household, the second stage could be estimated with household fixed effects. However, there is limited variation in education outcomes across children within a family and a second stage fixed effects specification is unable to estimate the coefficients of interest with any degree precision.

Table 6, columns (1) and (2), show that the 2SLS estimates of the effect of child labor on education are negative and statistically significant. A one standard deviation increase in child labor hours (5.7 hours) is associated with a decrease in half a year of schooling and an 8.8 percentage point reduction in the chance of completing primary school. These results are in line with those obtained for Vietnam by Beegle, Dehejia, and Gatti (2005). Both papers also find that IV effects are greater than OLS effects.

To the extent that families send the least gifted children to work and skills in the classroom and in the field are positively correlated, OLS would overestimate the impact of child labor on schooling, relative to the causal effect (as estimated by IV).[13] However, our results instead lend support to the view that families send their most gifted children to work. To the extent that children's work in response to an agricultural shock is critical to the household, parents may decide to use their most talented children. Another possibility is that there is significant attenuation bias in the result due to measurement error. This is not implausible: our measure of child labor (hours worked in the week prior to the survey) is likely to be very noisy.

In column (3), we see that child labor does not appear to be significantly associated with migration.[14] In contrast, column (4) shows that individuals who worked when young are significantly more likely to be farming in adulthood; a one standard deviation increase in child labor results in a 9 percentage point increase in the likelihood of farming in adulthood. The choice between farming cash or subsistence crops is, however, unaffected by working in childhood (column (5)) [15] Similarly, whether the individual had a wage or salary job in the past

[13] This validates one of the key predictions of the model presented in Horowitz and Wang (2004).
[14] Results do not change if we include in the sample the children who could not be recontacted between baseline and wave 5.
[15] Note that farming and working for a wage are not mutually exclusive. Of 1,318 people: 180 do neither; 142 working for wage/salary, not farming; 653 farming, not working for wage/salary; 343 both farming and working for wage/salary.

12 months is also not explained by child labor (column (6)). It is interesting to note that child labor is associated with a significant reduction in the marginal productivity of labor in agriculture (column (8)). A one standard deviation increase in child labor leads to a 23 percent reduction in the marginal productivity of labor in agriculture; this effect is significant at the 10 percent level.

Our result on the increased likelihood of farming can be rationalized in the Rosenzweig and Wolpin (1985) framework in which child labor imparts plot-specific experience that – as opposed to formal education – is difficult to transfer to other activities. An individual who works as a child thus benefits from locking himself into farming rather than seeking opportunities in other sectors or by migrating. Of course, one would have to believe that such plot-specific knowledge is not being picked up in our estimates of the marginal productivity of labor in agriculture, which goes down rather than up. Alternatively, our results on farming and the marginal productivity of labor could simply be viewed as implications of reduced education, which can both narrow opportunities outside the agricultural sector and – if education and labor are complementary in the production function – reduce the marginal productivity of labor.

Finally, in column (7), we find that child labor is associated with a significant increase in the probability of marriage. A one standard deviation (5.7 hour) increase in child labor leads to a 20 percentage point increase in the probability of marriage by wave 5. As noted in the discussion above, since marriage is almost universal in Kagera, this result suggests that child labor is associated with earlier marriage.

One of the most striking features of Table 7 is that splitting the results by gender reveals that the education result is driven by boys. One possible rationalization of this finding is that parents place a lower priority on the education of girls than boys. Alternatively, chores may be less harmful to education than agricultural work. As discussed in Section IV.2, Table 2 shows

that the incremental effect of crop shocks for girls is an increase in chore hours and a reduction in economic hours.

The one robustly significant effect of child labor for girls is on the probability of marriage, which is also positive and significant among boys. There are several possible interpretations of this. For instance, it is possible that the incremental work induced by our instrument (namely chores) makes girls more valuable on the marriage market. The marriage result for boys could similarly reflect the increased value on the marriage market of boys who have more agricultural experience or could also be the byproduct of reduced educational opportunities.

VI. Extensions and Robustness Checks

VI.1 Threshold effects in child labor hours

In this section we consider whether the negative effects of child labor estimated in Table 7 are truly linear or whether there are any threshold effects, i.e., levels of child labor beyond which we begin to see truly harmful effects but below which child labor is not particularly harmful. Table 8 presents five alternative specifications in which the child labor variable is coded as an indicator for having worked more than a specified cutoff: 0 hours per week, 6.5 hours per week (the 25th percentile), 15 hours per week (the median), 24 hours per week (the 75th percentile), and 35 hours per week (the 90th percentile).

It is noteworthy that simply working any level of positive hours does not have a statistically significant impact, other than on marriage. Of course, it must be noted that less than 10 percent of the population do not work, so the effect may not be estimated precisely. When child labor is coded as working more than 6.5 hours, the four most robust effects from the

previous specification (school years, primary schooling, farming, and marriage) now show statistically significant effects. The magnitude of the school effect is large even at the 25th percentile of child labor hours: a 40 percent (or 2.5 year) reduction in completed schooling.

As we increase the threshold for the child labor indicator the magnitudes of the effects increase. For example, for completed schooling, the effect increases from 3 to 3.9 to 5.6 years of schooling lost for having worked more than the threshold. For the higher thresholds, the negative effect on the marginal productivity of labor also begins to kick in as significant.

This exercise suggests that there are significant, negative effects of child labor from even moderate levels of intensity, but that the effects increase in magnitude with the intensity of child labor.

VI.2 Robustness checks: the full sample of children and adults

In this section, we check the sensitivity of our results to the choice of sample. As discussed in Section IV.1, the regressions in Tables 2-7 are estimated on the sample of 7 to 15 year olds who were either in school as of each wave or who were not in school but still young enough to start school at some later point (prior to turning 10). This restriction is particularly important for education outcomes because, while child labor and education are simultaneous decisions, we are interested in identifying the impact of child labor (rather than, say, delayed enrollment) on educational attainment. Including children who are unlikely ever to attend school (i.e. those older than 9 and not at school in wave 4) in the sample would naturally lead us toward finding a stronger negative impact of child labor on education.

When we run our instrumented regression on the full sample of children between ages 7 and 15 (Table 9, row 1), we find, as expected, larger coefficients for school years and primary

school completion. The marriage and farming results are unchanged, but the negative effect on the marginal productivity of labor is 5 percentage points smaller and no longer statistically significant. Given that we have added a number of children who were never attending school, the reduced negative effect on labor productivity suggests that the negative effect we were obtaining in Table 7 could reflect displaced education.

Next, we turn to the adult sample (individuals aged 20 and older in wave 1) as a comparison group for the child sample. In particular, we estimate the same two-stage least squares specification used for children on the adult sample, and also consider the difference between the estimated effect of work on children and adults. In Table 9, row 2, we see that there are significant negative effects on school years and the indicator for primary school, although the magnitudes of these effects are one third to one fifth of the magnitude of the children's effect. There are also significant and negative effects for cash crops and the estimated marginal productivity of labor. There are several possible interpretations. It is possible that there could, in fact, be a negative effect on schooling, since 71 members of the adult sample are in fact in school in wave 1. Alternatively, it is possible that there is a direct effect of the instruments being picked up by instrumented work hours, i.e., that the exclusion restriction fails.

Taking the second interpretation further, if we are willing to assume that the direct, non-excluded effect of the instruments is the same for adults and children, then we can difference the two sets of estimates to obtain the effect of child labor; these are presented in Table 9, row 3. As implied by the children's and adults' estimates, there continues to be a significant negative effect on school years and completion of primary school. These effects are naturally smaller than the previous estimates, but still substantial in magnitude: a 0.46 year (7.2 percent) loss in schooling for a one standard deviation increase in child labor hours and a 8 percentage point reduction in

the completion of primary school. Likewise, we continue to find positive effects on the probability of farming and marriage, which are comparable (indeed, greater) in magnitude to our previous estimates. Because the negative schooling effects for the adult sample could in fact be due to a reduction in education, we view the estimates in row 3 as being lower bounds for the child labor effect.

VI.3 Robustness: magnitude of the shock

Finally, we exploit cross-sectional variation in the size of shocks to test whether our second stage results are driven by large shocks or whether we obtain similar results for smaller shocks. As discussed in Section IV.2, we are more confident that the exclusion restriction required for a valid instrumental variable (namely that the instrument affects the outcome only through the endogenous variable) will be satisfied for small shocks, which are less likely to imply direct long lasting effects on household outcomes. In Table 10, we re-estimate our results, using three alternative definitions of the shock (an agricultural shock that results in a loss of respectively at most 5, 10 and 20 percent of the crop) and excluding those individuals who experienced shocks larger than the respective thresholds (for example at the 20 percent threshold we exclude 71 individuals from our original sample who experienced a crop loss of greater than 20 percent). With the exception of labor productivity, we find that our results are similar in magnitude and significance to our baseline specification in Table 6. This gives us additional confidence in interpreting our results for education, farming, and marriage causally, and suggests that some caution is needed in interpreting the negative effect of child labor on adult labor productivity

VII. Conclusion and future research

In this paper we investigate the impact of child labor on education and labor market outcomes using panel data from the Kagera region of Tanzania. Building on our previous work, we use the occurrence of crop and rainfall shocks as instruments for child labor. In instrumental variables specifications, we find a negative and significant effect of child labor on school years and the probability of completing primary school 10 to 13 years later. Moreover, child labor is significantly positively associated with the probability of being a farmer.

The education results are mainly driven by the sample of boys. For girls we find a robustly positive effect on the probability of marriage and a somewhat less robust negative effect on the marginal productivity of labor. In conjunction with our finding that the extra child labor induced by crop shocks is primarily chores, this suggests the possibility that child labor pushes girls away from agriculture and toward household activities and marriage. In future work we intend to use data on bride prices to examine whether child labor in fact increases girls' value on the marriage market.

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Table 1: Summary statistics

	Mean	SD
Baseline sample		
Hours worked in last 7 days	16.79	13.42
Chore hours in last 7 days	10.54	9.05
Crop shock	0.34	0.47
Female	0.49	0.50
Age	10.91	2.60
Number of observations	4,746	
Panel sample: 1991-2004		
Mean hours at baseline	16.79	10.56
Mean hours (predicted) at baseline	16.85	5.73
Female	0.49	0.50
Age at wave 4 baseline	11.44	2.77
Age in 2004	22.65	3.17
Mother's education 1-6 years	0.36	-
Mother's education 7+ years	0.32	-
Father's education 1-6 years	0.43	-
Father's education 7+ years	0.32	-
Log per capita expenditure	10.91	0.81
Log per capita land value	10.05	2.21
Log per capita asset value	10.04	1.60
Crop shock	0.34	-
Rainfall deviation	-0.11	0.38
School years	6.36	2.77
Completed primary	0.78	0.41
Stayed in/near village	0.69	0.46
Farming in past 12 months	0.76	0.43
Growing cash crop	0.55	0.50
Wage/salary job in past 12 months	0.37	0.48
Married	0.51	0.50
Marginal product of labor	1,949	3,479
Number of observations	1,313	

Notes: Baseline sample is restricted to children in school at baseline or less than 10 years of age and not yet enrolled. It includes children who are measured up to 4 times in the baseline panel (1991-1994). Hours includes hours working in economic (income generating) activities and in chores. Panel sample is the subset of children in baseline sample who are re-interviewed in 2004.

Table 2: 1st Stage estimation of child labor hours

	(1)	(2)	(3)	(4)	(5)	(6)
	Total work hours	Chore hours	Chore hours: girls	Chore hours: boys	Economic hours: girls	Economic hours: boys
Crop shock	3.822	4.670**	-3.833	1.243	-5.447***	1.752
	(2.989)	(2.018)	(2.603)	(2.091)	(1.909)	(2.601)
Crop shock * age	-0.055	-0.297**	0.532***	0.040	0.424***	0.260*
	(0.191)	(0.117)	(0.156)	(0.124)	(0.135)	(0.147)
Age	5.979***	3.133***	2.121***	4.260***	3.086***	2.582***
	(0.723)	(0.472)	(0.687)	(0.595)	(0.600)	(0.670)
Crop shock * Log land value	-0.276	-0.115	-0.144	-0.145	0.071	-0.422**
	(0.209)	(0.151)	(0.209)	(0.164)	(0.144)	(0.202)
Log per capita land value	0.538***	0.215**	0.407***	0.023	0.203*	0.429***
	(0.129)	(0.090)	(0.120)	(0.110)	(0.105)	(0.089)
Crop shock * Female	-14.579***	-12.172***				
	(2.574)	(1.770)				
Female	1.874***	2.962***				
	(0.496)	(0.351)				
Crop shock * Female * Age	1.344***	1.134***				
	(0.244)	(0.163)				
Rainfall deviation	0.953	0.541	0.272	0.741*	0.950*	0.003
	(0.589)	(0.398)	(0.609)	(0.423)	(0.484)	(0.599)
Age squared	-0.204***	-0.098***	-0.035	-0.166***	-0.115***	-0.095***
	(0.033)	(0.022)	(0.031)	(0.027)	(0.027)	(0.030)
Number of observations	4,746	4,746	2,325	2,421	2,325	2,421

Notes: Regressions from waves 1-4 at baseline for restricted sample of children described in text ages 7-15. Additional controls include age, age squared, household size, mother's education, father's education, log per capita household asset values, season dummies, and region dummies. Standard errors are in parentheses. *** indicates significance at 1%; ** at 5%; and, * at 10%. Work hours include hours working in economic (income generating) activities and in chores.

Table 3: Correlation between Instruments and Lagged Instruments and Household Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Crop shock	Crop shock	Crop shock	Rainfall deviation	Rainfall deviation	Rainfall deviation
Lagged shock, t-1		0.097	0.089			
		(0.076)	(0.076)			
Lagged shock t-2			0.040			
			(0.033)			
Lagged rainfall t-1					0.717***	0.824***
					(0.067)	(0.118)
Lagged rainfall t-2						-0.304
						(0.205)
Lagged rainfall t-3						-0.159
						(0.248)
Lagged rainfall t-4						0.012
						(0.147)
Household size	0.004	0.003	0.004	0.023	0.023	0.023
	(0.005)	(0.005)	(0.005)	(0.031)	(0.031)	(0.031)
Father's education 1-6 years	0.006	0.007	0.005	0.163	0.294	0.058
	(0.039)	(0.038)	(0.038)	(0.598)	(0.292)	(0.250)
Father's education 7+ years	0.002	-0.000	-0.007	-0.286	-0.259	-0.073
	(0.041)	(0.041)	(0.042)	(0.901)	(0.440)	(0.369)
Mother's education 1-6 years	-0.019	-0.021	-0.023	0.269	0.325	-0.081
	(0.038)	(0.039)	(0.039)	(0.439)	(0.214)	(0.201)
Mother's education 7+ years	-0.090*	-0.092**	-0.086*	0.831	0.556	0.346
	(0.046)	(0.047)	(0.048)	(1.000)	(0.489)	(0.424)
Number of observations	651	651	651	51	51	51

Notes: Regressions from waves 1-4 at baseline for restricted sample of children described in text ages 7-15. Additional controls include age, age squared, proportion of female household members, and season dummies. *** indicates significance at 1%; ** at 5%; and, * at 10%.

Table 4: Long-run shock effect on household wealth

	(1) Physical assets in wave 5 ('000 shillings)	(2) Business assets in wave 5 ('000 shillings)	(3) Durables assets in wave 5 ('000 shillings)	(4) Farm equipment in wave 5 ('000 shillings)	(5) Land in wave 5 ('000 shillings)	(6) Occupied dwellings in wave 5 ('000 shillings)
Crop shock	1,314	-70	69	-16.8	1,075	272
in waves 1-4	(1,623)	(102)	(76)	(12.1)	(1,486)	(483)
Rainfall deviation	-4,247	-665	-65	-8.7	-3,160	-381
	(3,559)	(630)	(61)	(9.8)	(3,533)	(287)
Number of observations	1,263	1,280	1,274	1,271	1,275	1,273

Notes: Controls include age, age squared, a sex dummy, mother's education, father's education, household size, and region dummies. Standard errors are clustered at the wave 1-4 household level.

Table 5: Impact of Child Labor in Waves 1-4 on Outcomes in Wave 5: OLS

	(1) School years	(2) Completed primary	(3) Stayed in/near village	(4) Farming in past 12 months	(5) Growing cash crop	(6) Wage/salary job in past 12 months	(7) Married	(8) Marginal productivity of labor
Boys and girls								
Mean child labor hours, waves 1-4	-0.008	-0.001	-0.001	0.001	0.002	-0.001	0.002	0.003
	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
% impact on outcome of 1 sd ↑ in hours	-0.7%	-0.7%	-0.8%	0.8%	2.1%	-1.6%	2.2%	1.7%
Level impact on outcome of 1 sd ↑ in hours	-0.05	-0.01	-0.01	0.01	0.01	-0.01	0.01	0.02
Number of observations	1,308	1,308	1,308	1,308	1,308	1,308	1,308	848
Girls								
Mean child labor hours, waves 1-4	-0.010	-0.002	-0.003	0.0001	0.001	0.0001	0.004**	0.006
	(0.014)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
% impact on outcome of 1 sd ↑ in hours	-1.0%	-1.6%	-2.9%	0.1%	1.1%	0.1%	3.7%	0.6%
Level impact on outcome of 1 sd ↑ in hours	-0.06	-0.01	-0.02	0.00	0.01	0.00	0.03	0.04
Number of observations	637	637	637	637	637	637	637	387
Boys								
Mean child labor hours, waves 1-4	-0.008	-0.0001	0.001	0.002	0.003	-0.002	-0.001	0.008
	(0.012)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
% impact on outcome of 1 sd ↑ in hours	-0.6%	0.1%	0.7%	1.4%	2.8%	-1.9%	0.1%	0.5%
Level impact on outcome of 1 sd ↑ in hours	-0.04	0.00	0.00	0.01	0.01	-0.01	0.00	0.04
Number of observations	671	671	671	671	671	671	671	461

Notes: Each cell presents results from a separate regression, with a common specification across sets of rows: all boys and girls between 7 and 15 who are in school or can enroll; all girls satisfying the same age and school criteria; and all boys satisfying the same age and school criteria. The magnitude of the effect is computed as the percentage and level impact on the outcome of a one standard deviation (5.7 hour) increase in child labor. Additional controls include a sex dummy, age, age squared, mother's education, father's education, region dummies, wave 1 log expenditure, wave 1 log assets, and wave 1 log land holdings.

Table 6: Reduced-Form Impact of Instruments in Waves 1-4 on Outcomes in Wave 5: OLS

	(1) School years	(2) Completed primary	(3) Stayed in/near village	(4) Farming in past 12 months	(5) Growing cash crop	(6) Wage/salary job in past 12 months	(7) Married	(8) Marginal productivity of labor
Shock								
Any shock, waves 1-4	-0.466**	-0.060*	-0.059	-0.021	-0.056	0.006	0.010	-0.124
(mean level of wave 1-4 shock = 0.17)	(0.206)	(0.033)	(0.039)	(0.034)	(0.037)	(0.032)	(0.035)	(0.088)
% impact on outcome of mean shock	-1.2%	-1.3%	-1.4%	-0.5%	-1.7%	0.3%	0.3%	-2.1%
Level impact on outcome of mean shock	-0.08	-0.01	-0.01	0.00	-0.01	0.00	0.00	-0.02
Number of observations	1,308	1,308	1,308	1,308	1,308	1,308	1,308	848
Rainfall								
Rainfall deviation, waves 1-4	-0.544**	-0.047	-0.060	-0.007	-0.046	0.015	0.072*	-0.071
	(0.259)	(0.040)	(0.038)	(0.036)	(0.037)	(0.033)	(0.042)	(0.096)
% impact on outcome of 1 sd ↑ in rain	-8.6%	-5.9%	-9.3%	-0.9%	-8.1%	7.4%	10.7%	-1.1%
Level impact on outcome of 1 sd ↑ in rain	-0.54	-0.05	-0.06	-0.01	-0.05	0.02	0.07	-0.07
Number of observations	637	637	637	637	637	637	637	387

Notes: Each cell presents results from a separate regression, with a common specification across sets of rows. The first set of rows includes any agricultural shock as a right hand side variable, and the second set of rows includes standardized rainfall. The magnitude of the effect is computed as the percentage and level impact on the outcome of the mean level of shocks in waves 1 to 4 (0.17) and one standard deviation rainfall variation respectively. Additional controls include a sex dummy, age, age squared, mother's education, father's education, region dummies, wave 1 log expenditure, wave 1 log assets, and wave 1 log land holdings.

Table 7: Impact of Child Labor: 2SLS of 2004 outcomes

	(1) School years	(2) Completed primary	(3) Stayed in/near village	(4) Farming in past 12 months	(5) Growing cash crop	(6) Wage/salary job in past 12 months	(7) Married	(8) Marginal productivity of labor
Boys and girls								
Mean child labor hours, waves 1-4	-0.097***	-0.012***	-0.008	0.012**	0.001	0.002	0.018***	-0.041*
	(0.028)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.023)
% impact on outcome of 1 sd ↑ in hours	-8.7%	-8.8%	-6.6%	9.1%	1.0%	3.1%	19.9%	-23.4%
Level impact on outcome of 1 sd ↑ in hours	-0.55	-0.07	-0.05	0.07	0.01	0.01	0.10	-0.23
Number of observations	1,308	1,308	1,308	1,308	1,308	1,308	1,308	848
Girls								
Mean child labor hours, waves 1-4	-0.045	-0.004	-0.010	-0.003	-0.004	0.008	0.021***	-0.017
	(0.036)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.016)
% impact on outcome of 1 sd ↑ in hours	-4.5%	-3.2%	-9.7%	-2.4%	-4.4%	24.6%	19.6%	-1.6%
Level impact on outcome of 1 sd ↑ in hours	-0.28	-0.03	-0.06	-0.02	-0.03	0.05	0.13	-0.11
Number of observations	637	637	637	637	637	637	637	387
Boys								
Mean child labor hours, waves 1-4	-0.186***	-0.022***	0.001	0.030***	0.010	-0.004	0.025***	-0.006
	(0.046)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.046)
% impact on outcome of 1 sd ↑ in hours	-14.5%	-14.2%	0.7%	20.5%	9.2%	-3.8%	34.0%	-0.4%
Level impact on outcome of 1 sd ↑ in hours	-0.92	-0.11	0.00	0.15	0.05	-0.02	0.12	-0.03
Number of observations	671	671	671	671	671	671	671	461

Notes: Each cell presents results from a separate regression, with a common specification across sets of rows: all boys and girls between 7 and 15 who are in school or can enroll; all girls satisfying the same age and school criteria; and all boys satisfying the same age and school criteria. The magnitude of the effect is computed as the percentage and level impact on the outcome of a one standard deviation (5.7 hour) increase in child labor. Additional controls include a sex dummy, age, age squared, mother's education, father's education, region dummies, wave 1 log expenditure, wave 1 log assets, and wave 1 log land holdings.

Table 8: 2SLS robustness checks: threshold effects of child labor hours

	(1) School years	(2) Completed primary	(3) Stayed in/near village	(4) Farming in past 12 months	(5) Growing cash crop	(6) Wage/salary job in past 12 months	(7) Married	(8) Marginal productivity of labor
Works more than 0 hours								
Mean child labor hours, waves 1-4	-0.929	-0.047	-0.532	0.476	0.812	-0.245	1.294***	-0.829
	(2.959)	(0.446)	(0.466)	(0.445)	(0.511)	(0.454)	(0.471)	(1.986)
% impact on outcome of working>0 hours	-14.6%	-6.0%	-76.6%	63.1%	146.7%	-66.6%	251.1%	-82.9%
Level impact on outcome of working>0 hours	-0.93	-0.05	-0.53	0.48	0.81	-0.25	1.29	-0.83
Number of observations	1,308	1,308	1,308	1,308	1,308	1,308	1,308	848
Works 6.5 hours or more (25th percentile)								
Mean child labor hours, waves 1-4	-2.577*	-0.315	-0.462*	0.418*	0.131	0.112	0.917***	-1.528
	(1.463)	(0.224)	(0.244)	(0.237)	(0.266)	(0.252)	(0.239)	(1.252)
% impact on outcome of working>6.5 hours	-40.6%	-39.7%	-71.4%	53.1%	23.0%	54.9%	135.8%	-23.0%
Level impact on outcome of working>6.5 hours	-2.58	-0.32	-0.46	0.42	0.13	0.11	0.92	-1.53
Number of observations	1,308	1,308	1,308	1,308	1,308	1,308	1,308	848
Works 15 hours or more (median)								
Mean child labor hours, waves 1-4	-3.005***	-0.347**	-0.198	0.392**	0.057	0.034	0.692***	-1.063
	(0.947)	(0.153)	(0.165)	(0.162)	(0.181)	(0.175)	(0.160)	(0.833)
% impact on outcome of working>15 hours	-47.2%	-45.1%	-26.7%	54.1%	10.6%	6.5%	190.3%	-14.4%
Level impact on outcome of working>15 hours	-3.01	-0.35	-0.20	0.39	0.06	0.03	0.69	-1.06
Number of observations	1,308	1,308	1,308	1,308	1,308	1,308	1,308	848

Table 8 (continued): 2SLS robustness checks: threshold effects of child labor hours

	(1) School years	(2) Completed primary	(3) Stayed in/near village	(4) Farming in past 12 months	(5) Growing cash crop	(6) Wage/salary job in past 12 months	(7) Married	(8) Marginal productivity of labor
Works 24 or more hours (75th percentile)								
Mean child labor hours, waves 1-4	-3.941***	-0.504***	-0.218	0.440**	-0.063	0.124	0.674***	-1.530*
	(1.053)	(0.168)	(0.192)	(0.190)	(0.205)	(0.205)	(0.184)	(0.805)
% impact on outcome of working>24 hours	-61.9%	-65.5%	-29.4%	60.7%	-11.7%	23.7%	185.3%	-20.7%
Level impact on outcome of working>24 hours	-3.94	-0.50	-0.22	0.44	-0.06	0.12	0.67	-1.53
Number of observations	1,308	1,308	1,308	1,308	1,308	1,308	1,308	848
Works 35 or more hours (90th percentile)								
Mean child labor hours, waves 1-4	-5.560***	-0.763***	-0.412	0.714**	0.073	0.092	0.783***	-2.236*
	(1.679)	(0.263)	(0.312)	(0.309)	(0.319)	(0.308)	(0.293)	(1.198)
% impact on outcome of working>35 hours	-87.3%	-99.2%	-55.6%	98.6%	13.6%	17.6%	215.3%	-30.2%
Level impact on outcome of working>35 hours	-5.56	-0.76	-0.41	0.71	0.07	0.09	0.78	-2.24
Number of observations	1,308	1,308	1,308	1,308	1,308	1,308	1,308	848

Notes: Each cell presents results from a separate regression, with a common specification across sets of rows. The first set of rows uses an indicator for having worked more than 0 hours to measure child labor. The second set of rows uses an indicator for having worked 10 or more hours per week, and the third set of rows uses an indicator for having worked 25 or more hours per week. The magnitude of the effect is computed as the percentage and level impact on the outcome of a one standard deviation (5.7 hour) increase in child labor. Additional controls include a sex dummy, age, age squared, mother's education, father's education, region dummies, wave 1 log expenditure, wave 1 log assets, and wave 1 log land holdings.

Table 9: 2SLS robustness checks

	(1) School years	(2) Completed primary	(3) Stayed in/near village	(4) Farming in past 12 months	(5) Growing cash crop	(6) Wage/salary job in past 12 months	(7) Married	(8) Marginal productivity of labor
All kids sample								
Mean child labor hours, waves 1-4	-0.127***	-0.015**	-0.007	0.009**	0.002	0.008	0.018***	-0.032
	(0.036)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.022)
% impact on outcome of 1 sd ↑ in hours	-11.4%	-11.0%	-5.7%	6.8%	2.1%	12.4%	19.9%	-18.2%
Level impact on outcome of 1 sd ↑ in hours	-0.72	-0.09	-0.04	0.05	0.01	0.05	0.10	-0.18
Number of observations	1,853	1,853	1,853	1,853	1,853	1,853	1,853	1,284
Adults (20 +)								
Mean child labor hours, waves 1-4	-0.035***	-0.003***	0.0001	0.0001	-0.002**	0.001	-0.0001	-0.007**
	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.003)
% impact on outcome of 1 sd ↑ in hours	-3.1%	-2.2%	0.1%	0.1%	-2.0%	2.8%	-0.01%	-0.6%
Level impact on outcome of 1 sd ↑ in hours	-0.20	-0.02	0.00	0.00	-0.01	0.01	0.00	-0.04
Difference								
Difference in mean child labor impact, waves 1-4	-0.092***	-0.012**	-0.007	0.0074***	0.004	0.007	0.018***	-0.025
	(0.04)	(0.0061)	(0.0051)	(0.0041)	(0.0051)	(0.01)	(0.01)	(0.02)
% impact on outcome of 1 sd ↑ in hours	-7.2%	-8.1%	-5.2%	7.3%	5.3%	7.2%	25.1%	-1.6%
Level impact on outcome of 1 sd ↑ in hours	-0.46	-0.06	-0.04	0.05	0.03	0.04	0.09	-0.12
Total observations	1,853	1,853	1,853	1,853	1,853	1,853	1,853	1,284

Notes: Each cell presents results from a separate regression, with a common specification across sets of rows. The all kids sample uses all children between 7 and 15 (hence adds those children 7 to 15 not in school in waves 1 to 4 excluded from the main specification). The adult sample uses all adults age 20 or more in waves 1 to 4. The final row presents the difference between the two estimates and the standard error of the difference. The magnitude of the effect is computed as the percentage and level impact on the outcome of a one standard deviation (5.7 hour) increase in child labor. Additional controls include a sex dummy, age, age squared, mother's education, father's education, region dummies, wave 1 log expenditure, wave 1 log assets, and wave 1 log land holdings.

Table 10: 2SLS robustness checks: magnitude of the shocks

	(1) School years	(2) Completed primary	(3) Stayed in/near village	(4) Farming in past 12 months	(5) Growing cash crop	(6) Wage/salary job in past 12 months	(7) Married	(8) Marginal productivity of labor
Crop shocks<5% of total								
Mean child labor hours, waves 1-4	-0.119***	-0.012**	0.004	0.021***	0.005	-0.003	0.027***	-0.009
	(0.035)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.034)
% impact on outcome of 1 sd ↑ in hours	-10.7%	-8.8%	3.3%	15.9%	5.1%	-4.7%	29.9%	-5.1%
Level impact on outcome of 1 sd ↑ in hours	-0.68	-0.07	0.02	0.12	0.03	-0.02	0.15	-0.05
Number of observations	1,186	1,186	1,186	1,186	1,186	1,186	1,186	800
Crop shocks<10% of total								
Mean child labor hours, waves 1-4	-0.119***	-0.013**	0.000	0.018***	0.004	-0.003	0.025***	-0.015
	(0.033)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.031)
% impact on outcome of 1 sd ↑ in hours	-11.8%	-10.3%	0.0%	14.4%	4.4%	-9.2%	23.3%	-1.4%
Level impact on outcome of 1 sd ↑ in hours	-0.75	-0.08	0.00	0.11	0.03	-0.02	0.16	-0.09
Number of observations	1,211	1,211	1,211	1,211	1,211	1,211	1,211	815
Crop shocks<20% of total								
Mean child labor hours, waves 1-4	-0.113***	-0.013**	-0.000	0.016***	0.003	0.001	0.025***	-0.033
	(0.032)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.030)
% impact on outcome of 1 sd ↑ in hours	-8.8%	-8.4%	0.0%	10.9%	2.8%	0.9%	34.0%	-2.2%
Level impact on outcome of 1 sd ↑ in hours	-0.56	-0.06	0.00	0.08	0.01	0.00	0.12	-0.16
Number of observations	1,239	1,239	1,239	1,239	1,239	1,239	1,239	834

Notes: Each cell presents results from a separate regression, with a common specification across sets of rows. The second set of rows codes the instrument as 0 if the household did not experience a shock and 1 if it experienced a shock of 5 per cent or less of total crop. The second set of rows codes the instrument as 0 if the household did not experience a shock and 1 if it experienced a shock of 10 per cent or less of total crop. The second set of rows codes the instrument as 0 if the household did not experience a shock and 1 if it experienced a shock of 20 per cent or less of total crop. Each set of rows excludes those observations with shocks greater than the specified cutoff. The magnitude of the effect is computed as the percentage and level impact on the outcome of a one standard deviation (5.7 hour) increase in child labor. Additional controls include a sex dummy, age, age squared, mother's education, father's education, region dummies, wave 1 log expenditure, wave 1 log assets, and wave 1 log land holdings.