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

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I. Introduction

This paper exploits a unique long-horizon longitudinal data set from Tanzania to examine the long-run consequences of child labor on education, employment choices, and marital status. The question we examine is important for many reasons. The assumption that child labor is harmful to children's development underpins both the theoretical literature and the policy debate. For example, from the policy perspective, there is a general perception that the worldwide returns to eliminating child labor are very large (see International Labour Organization [ILO], 2003). However, the evidence that rigorously quantifies the consequences of child labor is limited. Both theoretically and empirically, it is not clear whether child labor substantially displaces schooling. In rural settings in developing countries (and more than 70 percent of child labor in developing countries is rural; ILO, 2002), both school and child labor tend to be low-intensity activities, in contrast to the sweatshops and full-time work that characterize child labor in the popular imagination and which have existed historically in some urban settings in North America and Europe (see Basu, 1999). Furthermore, even if child labor does disrupt schooling, it presumably also provides the child with labor market experience that subsequently could lead to increased earnings. Which effect dominates is an empirical matter.

A growing empirical literature (reviewed in Section 2) analyzes the relationship between child labor and school attainment but, with a few exceptions, this literature examines the correlation, not the causal relationship, between these variables. There are many reasons to doubt a causal interpretation of the correlation between child labor and education. Households that resort to child labor presumably differ along an array of dimensions, both observable (education, wealth, occupation) and unobservable (social networks, concern for children, etc.), from those that do not. Even within households, children's ability is unobserved to the econometrician but observable to parents. To the extent that parents send their least (most) motivated children to work, this would generate a negative (positive) correlation between child labor and school attainment simply based on selection.

Beegle, Dehejia, and Gatti (2005) estimate the causal impact of child labor on education attainment, earnings, and health using two rounds of panel data from the Vietnam Standard Living Survey. We instrument for participation in child labor by using community shocks and rice prices, two variables that influence child labor but are plausibly exogenous with respect to household choices. With this strategy we estimate that, over the 5-year period spanned by our panel, the mean level of child labor reduces the probability of being in school by 30 percent and educational attainment by 6 percent. Indicators of health were not in general affected by child

labor status. However, children who have experienced child labor are more likely to be working for wages five years later, and also have higher daily earnings (including both actual wages and estimated farm wages). These estimates are significant at standard levels, and suggest that the returns to work experience are higher than the returns to schooling and that, overall, child labor might amount to a net benefit for children, at least until early adulthood. Using data on adults to simulate the future impact of child labor on current children, we find that returns to education increase with age, whereas returns to experience decline monotonically; the net present discounted value of child labor is positive for households with a discount rate of 11.5 percent or higher.

Although the empirical strategy employed in Beegle, Dehejia, and Gatti (2005) tries to overcome some of the limitations of the existing literature, the 5-year interval between the two rounds of data limits us to extrapolating the long-run effects of child labor rather than estimating it. Conversely, with the Kagera data we can measure outcomes 10-13 years after child labor has taken place. In a previous paper we have documented the extent to which families use child labor in the Kagera region as a means to cope with agricultural shocks (Beegle, Dehejia, and Gatti, 2006). In a sample of 7 to 15 year olds, we find that crop shocks (as measured by crop accidentally lost to pests, insects, and fire) lead to a significant increase in the level of child labor and that households with assets are able to offset approximately 80 percent of this shock. Educational enrolment decreases in response to shocks, although households with a typical level of asset holdings are able to fully offset this effect. These results suggest that poorer households might be using assets as a buffer stock, drawing them down in times of need, whereas wealthier households' behavior is consistent with an access to credit story. More importantly, given their characteristics, these shocks are plausible candidates to serve as instruments for participation in child labor: they are good predictors of child labor and, as they are not correlated over time within households, they appear to be exogenous at the household level (see detailed discussion in Section IV).

Our 2SLS estimates indicate that child labor is causally associated with reduced educational attainment (both as measured by the number of school years as well as by an indicator capturing completion of primary school). Interestingly, this result appears to be entirely driven by the sample of boys, for whom doubling labor hours from a mean prevalence (16 hours) would imply losing 80% of a school year. Boys who worked when young are more likely to be farming (as opposed to earning a wage), although we could not find evidence that child labor is associated with discernible differences in the choices of crop (cash versus subsistence) or with `subsequent migration. For girls, the main discernable effect is on marriage: a higher level of

child labor hours is associated with a substantially greater chance of being married 10 to 13 years later.

The paper is organized as follows. Section II briefly reviews the existing literature. Section 3 introduces the data, and Section 4 describes the empirical methodology and discusses in detail the plausibility of our instrumental variable approach. Results are discussed in Section 5. Section 6 concludes.

II. Literature Review

There is a large literature that examines the tradeoff between child labor and schooling. In this section, we highlight a few of the existing results. 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) estimate this relationship directly, and show that child work is a significant negative predictor of age-grade distortion. Akabayashi and Psacharopoulos (1999) show that in addition to school attainment, children's reading competence (as assessed by parents) decreases with child labor hours. Finally, Heady (2003) uses objective measures of reading and mathematics ability and finds a negative relationship between child labor and educational attainment in Ghana.

The papers reviewed thus far examine the correlation between child labor and schooling, rather than the causal relationship. As we discuss in detail below, there are many reasons to doubt that these two coincide. A few recent papers address this issue. Using data from Ghana, Boozer and Suri (2001) exploit regional variation in the pattern of rainfall as a source of exogenous variation in child labor. They 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 a significantly negative effect of child labor on educational performance. Ray and Lancaster (2003) instrument child labor with household measures of income, assets, and infrastructure (water, telephone, and electricity) to analyze its impact on several school outcome variables in seven countries. Their findings generally indicate a negative impact of child labor on school outcomes.[1] However, their two-stage strategy is questionable, as it relies on the strong assumption that household income assets and infrastructure satisfy the exclusion restriction in the schooling equations. Finally, Ravallion and Wodon (2002) indirectly assess this relationship in their study of a food-for-school program in Bangladesh that exploits between-village variation in program

[1] 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.

participation. They find that the program led to a significant increase in schooling, but that only one eighth to one quarter of the increased schooling hours seem to have come from decreased child labor. This suggests that child labor does not lead to equal reductions in schooling.

The link between child labor and subsequent labor market outcomes is examined by Emerson and Souza (2006). They examine the effect of child labor and child schooling on adult outcomes. Using an instrumental variable strategy, they argue that, even controlling for completed schooling, child labor has a negative effect on adult earnings. Their instruments for child labor and child schooling include the number of schools per child in the state, the number of teachers per school, and GDP per capita at age 12. Their paper has a number of potential strengths (a large, nationally representative data set), but also potential weaknesses: the key child labor question is retrospective and is asked only to those individuals who are working as adults.

Krutikov (2006) uses the same data as our analysis. She focuses on education 10-13 years after the initial child labor as the outcome, and builds on the design suggested by Beegle, Dehejia, and Gatti (2006) by using shocks in the early rounds of the Kagera data as instruments for child labor. She finds significant, negative effects of shocks on education. The present paper builds on and extends this in a number of important directions. First, we examine several outcomes associated with child labor: wages, occupational choice, schooling, and marital status. We also use information on farming to estimate a simple agricultural production function (this is work in progress). Second, we address some potentially important sources of bias in Krutikov's results. We provide evidence for the plausibility of the exclusion restriction by estimating the reduced form effect of the instruments (crop shocks) on a range of the long-run outcome variables. We also use a more refined specification that includes a single endogenous variable (hours worked) and excludes from the sample children that, as of the baseline, had little or no chance to enter schooling (i.e. older children who had never attended school at the baseline; see the discussion below). We also correct some potentially significant econometric limitations of her design (in particular, the use of household level instruments in a second-stage regression that includes household fixed effects). Finally, we investigate whether child labor has different effects on boys and girls.

The literature investigating other medium and long run consequences of child labor is scant, mostly because of data constraints. As discussed in the introduction, Beegle, Dehejia, and Gatti (2005) investigates the causal impact of child labor on education, labor market outcomes, and health in Vietnam. In a sample of children from rural areas, increasing child labor by the average number of hours is associated, 5 years later, with a half–year reduction in schooling, with no significant impact on the prevalence of illness, and with a substantial increase in farm wages

(as measured by the estimated shadow farm wage). Using the same data and an instrumental variable technique, O'Donnell *et al.* (2003) investigate the impact of child labor on health outcomes. Their results differ in part from ours, as they find some evidence that work during childhood has a negative impact on health outcomes five years later.[2]

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 in northwest Tanzania (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 based on the 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 order to capture a higher percentage of households with a death while retaining a control group of households without a death.

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 as done 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, we anticipated that a considerable number of individuals would have migrated from the dwelling occupied in 1991-1994. A 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.

[2] See Beegle, Dehejia, and Gatti (2005) for a detailed discussion of this discrepancy.

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 (see details on the sample restriction in 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 for two reasons. First, the concept of child labor (by ILO standards) is not restricted to only economic activities.[3] Second, in the largely rural sample of households in this study, it may be difficult to distinguish time in household chore activities and time spent preparing subsistence food crops. Children in the sample work on average a total of 16 hours per week, of which 10 are chores (Table 1). Girls spend on average 2.5 hours more time working on household chores than boys, and this difference is more pronounced for older girls.

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 6.3 years of schooling and 78% of them have completed primary school.

We can measure labor market outcomes with an array of different variables. As the economy in the Kagera region is based mainly on extensive farming, an important indicator of success is whether the individual earns a salary or if he or she is involved in cash cropping (mainly tobacco and coffee) rather than subsistence farming. Moreover, the literature indicates that child labor might help a child acquire plot-specific experience, which could be particularly important in rural economies (Rosenzweig and Wolpin, 1985). If this is the case, we should expect child labor to be associated with a lower level of individual mobility, if plot-specific

[3]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 (perhaps impossible) to appropriately isolate the portion of time spent working on the farm that qualifies under this very nuanced definition.

experience cannot easily be exported to other agricultural contexts. We therefore investigate if child labor has an impact on the probability that individuals moved from their villages. This is possible because, unlike most of other surveys, the Kagera survey tracks individuals. In wave 5, 70% of the re-interviewed individuals in the sample were still living in the same or in neighboring villages. On the other hand, mobility is associated with significantly higher income gains for panel respondents (Beegle, De Weerdt and Dercon, 2006b). So, while there may be advantages to experience on specific farm plots, on the other hand, lower mobility may hinder economic growth for these children.

Finally, we explore whether child labor significantly affects marriage status. This is particularly interesting for our sample of girls, who tend to work more hours than boys, especially in household chores.[4] Since marriage is universal in Tanzania, we are effectively examining the influence of child labor on the likelihood of earlier marriage. Although we do not assume that marriage yields positive outcomes for those who marry, the work is motivated by the perception that the age at marriage can have significant effects on the future lives of women and their children.[5] Younger marriages increase health risks for women as well as potentially result in "worse" marriage matches.[6]

IV. Empirical Methodology

In order to estimate the long-run implications of child labor as risk a coping strategy, we combine three key pieces of information into our specification The realized risk in our study is a measure of agricultural shocks detailed in our previous work: the magnitude and frequency of crop lost accidentally to pests and fire in our baseline data ($S_{i,t}$). Child labor is defined as having worked in the baseline rounds (T_i). Our long-run outcomes of interest (Y_i) include completed education attainment, occupation, and marital status. Thus our basic specification is a two-stage least squares procedure of the form:

$$T_{i,t} = a + bS_{i,t} + cX_{i,t} + v_{i,t} \quad (1)$$

[4] For example, girls between 10 and 15 work 22 hours per week (15 of which are for house chores), against 18 hours for boys (11 of which are for house chores).

[5] Berhman et al. (2006) establish a casual nexus between education and age at marriage.

[6] 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.

$$Y_{i,\,t+10} = \alpha + \beta \hat{T}_{i,t} + \gamma X_{i,t+10} + \varepsilon_{i,t+10}, \tag{2}$$

where X_i are household and community-level controls and the shocks, $S_{i\ t}$, function as instrumental variables.

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 labor among younger children is low. Likewise, by some definitions, labor at age 14 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 as of wave 4. When we tabulate this variable, we find that only 32% of 7-8 year olds have been in school at some point in time, consistent with generalized delay in enrollment, while about 12% of children age 13 and above have never been to school. It is unlikely that these older children will enroll in the future. At the same time, the data show that, in response to a shock, households are more likely to employ the labor of the older, more productive children (see results in Table 2). Because of this, if we included 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 have not yet entered school but are still young enough to have a chance to enroll (7-9 year olds).

While shocks are reported at the household level, they do vary across the 4 baseline rounds of data, allowing us, in principle, to address both between- and within-household selection. In our earlier work, we provide evidence that the shocks are important predictors of child labor, but are also transitory (they are not correlated over time in each household) and, by capturing accidental losses of crop, they are reasonably exogenous to unobserved family characteristics and to outcomes realized 10-13 years later.

Beegle, Dehejia, and Gatti (2006) show that the extent to which households use child labor in response to shocks varies according to whether families have enough assets to buffer the impact of the shock. Moreover, as mentioned above, families tend to use the labor of older children. Thus, our main identifier (an indicator variable for whether a shock occurred in a family in a certain wave) is interacted both with the (log) level of durable assets, as in Beegle, Dehejia, and Gatti (2006), and with the child's age. In particular, our first-stage specification is

$$\begin{aligned} T_{ijt} = \alpha_j + \delta_t + \gamma_w + \beta_1 X_{ijt} + \beta_2 \cdot S_{jt} + \beta_3 (S_{jt} \cdot A_{jt}) \\ + \beta_4 \cdot A_{ijt} + \beta_5 (S_{jt} \cdot Age_{ijt}) + \beta_6 \cdot Age_{ijt} + \varepsilon_{ijt} \end{aligned} \tag{3}$$

where α_j, δ_t, and γ_w are household, time (season), and survey-round fixed effects respectively, and predicted hours estimated for individual i in household j at time t.

Our previous work, as well as the estimates on the sample used in this paper, confirms that these instruments are reasonable predictors of child labor. Table 2 reports estimates from a first-stage regression, where total child labor hours (column 1) and chore hours (column 2) are regressed on the instruments and other regressors (such as gender, region, age squared, and log per capita expenditure). In both cases the F-statistics for the instruments is about 4. The occurrence of a shock is associated with an average increase of about 4 working hours for a 10 year old child.

An important issue to be addressed in this context is if it is plausible that crop shocks satisfy the exclusion restriction. This is inherently challenging because an influential strand of literature suggests that transitory shocks can have long term consequences for households (see, for example, Ravallion and Lokshin, 2005). From our previous work, we know that these shocks are not correlated at the household level, and they do not seem to reflect household-specific characteristics. We also explored the contemporaneous effects of these shocks on household wealth, and found that shocks are not significantly associated with a decrease in cash per capita and physical assets per capita, although we found a negative and significant effect on durable assets, stronger for poorer households.

However, even if these shocks show little contemporaneous effects besides that on child labor and durable assets, they might directly affect long-run outcomes if short-run coping strategies such as child labor cannot be maintained over time. In order to investigate the extent of the concern, we look at reduced forms and assess the direct impact of the shocks on a wide range of outcomes 10+ years later.[7] In particular we regress wave 5 measures of household wealth, including (log) values of physical and business assets, durables, farm equipment, land, and occupied dwellings on shocks while controlling, linearly and interactively, for initial wealth defined as the initial value of the same variable in wave 1. Results are reported in Table 3. Shocks and their interaction with initial wealth are not significantly associated with changes in outcomes in any of these regressions. To further refine this investigation, in future work, we will exploit the differential impact (if any) of small and large shocks. If there does not appear to be substantial effects of the shocks in the long run, an instrumental variable strategy might be justified. Moreover, we could compare the impact of shocks between families with children and families without children to assess the extent to which channels other than child labor are at work in adjusting to these shocks. This is work in progress.

[7] This could be extended by verifying that shocks are not correlated with such causes of attrition in the sample through mortality and destitution.

V. Results

V.1 Baseline OLS estimation

We first present the results of OLS regressions of our main outcomes, as measured in wave 5, on average child labor over waves 1-4 (Table 4). Although we are aware that in this context OLS estimates are likely biased due to unobservables, we use them as baseline estimates.

Child labor (as measured by the average number of hours worked by each child in the 4 baseline waves) is significantly associated with reduced schooling and a reduced chance of completing primary education. In particular, doubling labor hours from the mean prevalence is associated with losing one quarter of a school year or a 3 percentage points reduced chance of completing primary education. As we include (log) per capita expenditure in specification, the regression controls cross-sectionally for relative economic status; thus, it is unlikely that in this context child labor hours simply proxy for poverty. However, because of the potential biases due to unobserved between and within household variation (which could result in a negative or positive bias) we are reluctant to draw causal inferences from these coefficients. None of the other variables seem to be significantly associated with child labor (Table 4).

When we split the sample by gender, the education effect is driven by the sample of boys, for whom doubling labor hours is associated with a decrease in schooling of about 80% of a year. Among girls child labor is associated with greater chance of marriage, which, given the sample characteristics most likely means a greater chance of marrying young (Table 5).

V.2 Instrumental variable estimation

We now discuss the results of estimating the impact of child labor hours on outcomes using a two stage least squares procedure. In the first stage, labor hours are predicted from a fixed effects regression of child labor hours on shocks and their interactions (equation (3) above). We average out the 4 values obtained for each child (one per wave) into a summary measure of average child labor per child. Predicted values of child labor are then used in the second stage of the regression, where standard errors corrected for the use of predicted hours (currently using a bootstrap procedure).[8].

[8] 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, the variation of education outcomes across children within a single family is low and a second stage fixed effect specification is unable to estimate any of the seven coefficients of interest with any degree precision.

In the education regressions, the 2SLS estimation returns significant negative coefficients on predicted child labor hours, which are twice the size of those estimated with OLS. According to these estimates, doubling child labor hours is associated with a decrease in a half year of schooling and a 6 percentage point reduced chance to complete primary school. These results are in line with those in Beegle, Dehejia, and Gatti (2005), where we had found that doubling average work hours (7 extra hours in that sample) was associated with a similar decline in school attainment. In both papers we find 2SLS effects are greater than OLS effects. To the extent that families send the less academically gifted children to work (and child ability is unobservable), OLS should overestimate the impact of child labor on schooling relative to the causal effect (as estimated by IV). Our results instead lend support to the view that families send their more academically gifted children to work (possibly because they are also more productive). This also validates one of the key predictions of the model presented in Horowitz and Wang (2004).

Child labor does not appear to be associated with migration. This finding provides indirect evidence for the fact that the experience gained through child work (as opposed to education) does not seem to be portable. However, individuals who worked more when young are more likely to be farming although they are equally likely to farm a cash crop as a subsistence crop. They are no more likely to be wage earners.[9] Note that here we are estimating a reduced form regression that already encompasses the impact of child labor on educational achievement. As with OLS, more child labor is associated with an increased chance of marriage.

In line with our OLS results, we find that the results for education and farming are driven by boys and the results on marriage are driven by girls.

VI. Discussion and future research

Overall our results show a significant negative effect of child labor 10 to 13 years after the fact. For boys, we find a significant reduction in education (an 8 percent reduction in school attainment at the mean level of child labor hours), and a significant increase in the probability of farming. This suggests the possibility that the extra farm labor associated with a shock induces specific experience that ties children more closely to the land, an interpretation which is

[9] Note that farming and working for a wage are not mutually exclusive:

Farming	Wage/salary job 0	1	Total
0	180	142	322
1	653	343	996
Total	833	485	1,318

consistent with Foster and Rosenzweig and Wolpin (1985). For girls, the only significant effect is on marriage, which suggests the possibility that child labor increases girls' value on the marriage market. This is consistent with the finds of Behrman et al. (2006).

There are a number of important extensions and robustness checks that can improve on the existing structure of the paper. Specifically, we are planning to further (indirectly) check the validity of our instruments. By exploiting the variation in the size of shocks (for example, using the share of crop lost over the total) to verify that large shocks do not have permanent effects on household wealth. One could also verify if the shocks have differential effects in families with and without children (which cannot resort to child labor as a coping mechanism). Moreover, we will experiment with an alternative set of instruments and use rainfall variation to identify participation in child labor. Rainfall is an obviously exogenous shock and data are available on a monthly basis for 21 stations over the 4 baseline waves. As identification could be less precise in this context, we can exploit variation in the month of interview as well as interact rainfall with relevant household and individual level variables to obtain a sufficiently precise identification at the individual level.

In specifying the treatment, we will experiment with hours spent in economic activities versus hours spent doing household chores for the whole sample and for boys and girls separately. To the extent that economic activity and chores differ, we might find different patterns for boys and girls.

We are also planning to enrich our set of outcomes by estimating an agricultural production function and recovering shadow wages (as in Beegle et al, 2005 and, originally, Skoufias, 1993).

Finally, we will purse a range of further robustness checks on the main specification (both when estimated with OLS and IV). So far we use a parsimonious specification that controls for main individual level correlates (age and gender) and (log) per capita expenditure but other omitted variables could be relevant in the specifications estimated in Tables 4 and 6.

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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
Any crop lost	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	8.44
Female	0.49	0.50
Age at wave 4 baseline	11.44	2.77
Age in 2004	22.65	3.17
2004 Outcomes:		
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
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) Hours	(2) Chore hours
Any crop lost	-0.727	1.940
	(3.078)	(2.018)
Asset value (log per capita)	0.553*	0.496**
	(0.268)	(0.175)
Assets * any crop lost	-0.419	-0.340*
	(0.267)	(0.175)
Any crop lost * age	0.478***	0.170*
	(0.143)	(0.094)
Female	1.767***	3.093***
	(0.425)	(0.279)
Age	6.781***	3.736***
	(0.732)	(0.480)
Age squared	-0.231***	-0.118***
	(0.033)	(0.022)
Dad:1-6 yrs of education	-0.399	-0.684
	(1.245)	(0.816)
Dad:7 yrs of education	0.073	-0.452
	(1.281)	(0.840)
Dad:8+ yrs of education	0.446	0.046
	(1.639)	(1.075)
Mom:1-6 yrs of education	-0.290	0.592
	(1.056)	(0.692)
Mom:7 yrs of education	-0.583	0.241
	(1.024)	(0.672)
Mom:8+ yrs of education	-0.464	1.398
	(2.522)	(1.654)
Number of observations	4,746	4,746

Notes: Household-fixed effects regressions from waves 1-4 at baseline for restricted sample of children described in text ages 7-15. Standard errors are in parentheses. *** indicates significance at 1%; ** at 5%; and, * at 10%. Hours includes hours working in economic (income generating) activities and in chores.

Table 3: Long-run shock effect on household wealth

	(1) Physical assets	(2) Business assets	(3) Durable assets	(4) Farm equipment	(5) Land	(6) Occupied Dwelling
Shock between Waves 1-4	-1.658	-0.014	-0.183	1.448	-0.227	0.439*
	(1.844)	(0.345)	(0.523)	(1.467)	(1.577)	(0.211)
Asset value (wave 1)	0.176	0.019	0.082	0.192	-0.014	0.151***
	(0.125)	(0.052)	(0.054)	(0.121)	(0.129)	(0.041)
Asset value * shock	0.123	0.057	0.097	-0.186	0.009	-0.105*
	(0.141)	(0.063)	(0.061)	(0.161)	(0.143)	(0.048)
Number of Observations	2,101	2,101	2,101	2,101	2,101	2,101

Notes: Household-level regressions of log asset value in 2004 on shocks during baseline and wave 1 log asset value. Asset values are measured in 2004 prices. Standard errors are in parentheses. *** indicates significance at 1%; ** at 5%; and, * at 10%.

Table 4: Impact of Child Labor: OLS 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
Mean hours at baseline	-0.011	-0.001	-0.001	0.001	0.001	-0.001	0.002
	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	0.012	0.027	-0.095***	0.061*	0.031	-0.315***	0.313***
	(0.148)	(0.023)	(0.026)	(0.024)	(0.027)	(0.025)	(0.024)
Age	0.025	-0.001	-0.064	0.061	0.020	0.046	0.081*
	(0.240)	(0.039)	(0.047)	(0.043)	(0.049)	(0.049)	(0.043)
Age squared	0.007	0.001	0.003	-0.003*	-0.002	-0.001	-0.001
	(0.010)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dad:1-6 yrs of education	0.297	0.034	0.036	0.009	0.010	0.049	-0.052
	(0.288)	(0.044)	(0.043)	(0.037)	(0.044)	(0.042)	(0.046)
Dad:7 yrs of education	1.160***	0.131**	-0.021	-0.070	-0.044	0.057	-0.113*
	(0.294)	(0.044)	(0.049)	(0.043)	(0.046)	(0.043)	(0.049)
Dad:8+ yrs of education	1.480***	0.138*	-0.012	-0.083	-0.081	0.072	-0.097*
	(0.375)	(0.054)	(0.061)	(0.060)	(0.062)	(0.057)	(0.059)
Mom:1-6 yrs of education	0.380*	0.063*	-0.051	-0.064*	-0.042	-0.072*	-0.046
	(0.223)	(0.032)	(0.035)	(0.032)	(0.036)	(0.036)	(0.033)
Mom:7 yrs of education	0.727**	0.080*	-0.081*	-0.032	-0.053	-0.059	-0.064*
	(0.241)	(0.036)	(0.038)	(0.034)	(0.041)	(0.039)	(0.038)
Mom:8+ yrs of education	1.738**	0.112	-0.262*	-0.174	-0.231*	-0.096	-0.128
	(0.621)	(0.068)	(0.146)	(0.125)	(0.118)	(0.100)	(0.086)
Ln Per cap exp., wave 1	0.493**	0.025	-0.005	-0.062*	-0.020	-0.014	-0.032
	(0.162)	(0.024)	(0.027)	(0.025)	(0.027)	(0.021)	(0.025)
Number of observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313

Notes: OLS estimates. Standard errors are in parentheses. *** indicates significance at 1%; ** at 5%; and, * at 10%. District dummies are included but not reported.

Table 5: Impact of Child Labor: OLS of 2004 outcomes, Females

	(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
Mean hours at baseline	-0.011	-0.002	-0.003	0.000	0.000	0.001	0.004*
	(0.013)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	0.238	0.015	-0.069	0.077	0.067	0.033	0.178**
	(0.381)	(0.060)	(0.073)	(0.060)	(0.070)	(0.062)	(0.066)
Age squared	-0.003	0.001	0.003	-0.004	-0.004	-0.001	-0.006*
	(0.017)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Dad:1-6 yrs of education	-0.071	-0.024	0.068	0.030	-0.002	0.094*	-0.012
	(0.380)	(0.058)	(0.067)	(0.048)	(0.057)	(0.046)	(0.063)
Dad:7 yrs of education	1.157**	0.102*	-0.002	-0.091	-0.127*	0.035	-0.109
	(0.392)	(0.057)	(0.074)	(0.058)	(0.063)	(0.048)	(0.067)
Dad:8+ yrs of education	0.932*	0.038	0.003	-0.063	-0.124	0.052	-0.114
	(0.454)	(0.067)	(0.087)	(0.075)	(0.079)	(0.064)	(0.078)
Mom:1-6 yrs of education	0.208	0.026	-0.046	-0.102**	-0.056	-0.019	-0.034
	(0.298)	(0.044)	(0.048)	(0.039)	(0.047)	(0.043)	(0.045)
Mom:7 yrs of education	0.639*	0.080*	-0.047	-0.068	-0.029	0.000	-0.085*
	(0.319)	(0.047)	(0.054)	(0.043)	(0.055)	(0.047)	(0.049)
Mom:8+ yrs of education	1.498*	0.058	-0.230	-0.234	-0.151	-0.042	-0.045
	(0.841)	(0.097)	(0.164)	(0.159)	(0.153)	(0.118)	(0.129)
Ln Per cap exp., wave 1	0.212	-0.004	-0.004	-0.088**	-0.041	-0.004	-0.041
	(0.220)	(0.033)	(0.037)	(0.033)	(0.037)	(0.028)	(0.033)
Number of observations	640	640	640	640	640	640	640

Notes: OLS estimates. Standard errors are in parentheses. *** indicates significance at 1%; ** at 5%; and, * at 10%. District dummies are included but not reported.

Table 6: 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
Mean hours (predicted) at baseline	-0.033*	-0.004*	-0.000	0.004*	0.001	-0.000	0.004*
	(0.012)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	0.040	0.031	-0.095***	0.058*	0.031	-0.316***	0.310***
	(0.150)	(0.023)	(0.024)	(0.025)	(0.025)	(0.025)	(0.024)
Age	0.106	0.011	-0.066	0.052	0.021	0.044	0.074*
	(0.239)	(0.039)	(0.045)	(0.047)	(0.050)	(0.048)	(0.039)
Age squared	0.005	0.001	0.003	-0.003	-0.002	-0.001	-0.001
	(0.010)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dad:1-6 yrs of education	0.273	0.030	0.036	0.012	0.011	0.050	-0.049
	(0.289)	(0.047)	(0.044)	(0.038)	(0.037)	(0.044)	(0.043)
Dad:7 yrs of education	1.156***	0.130*	-0.021	-0.069	-0.045	0.058	-0.113*
	(0.280)	(0.046)	(0.043)	(0.046)	(0.048)	(0.045)	(0.044)
Dad:8+ yrs of education	1.457***	0.135*	-0.011	-0.081	-0.081	0.073	-0.094*
	(0.352)	(0.060)	(0.053)	(0.060)	(0.059)	(0.058)	(0.053)
Mom:1-6 yrs of education	0.363	0.060*	-0.052	-0.062	-0.042	-0.072*	-0.044
	(0.226)	(0.034)	(0.032)	(0.037)	(0.037)	(0.035)	(0.033)
Mom:7 yrs of education	0.735**	0.081*	-0.082*	-0.033	-0.052	-0.060	-0.064
	(0.230)	(0.039)	(0.036)	(0.036)	(0.040)	(0.037)	(0.038)
Mom:8+ yrs of education	1.621*	0.096	-0.259	-0.162	-0.232*	-0.092	-0.116
	(0.618)	(0.069)	(0.158)	(0.140)	(0.120)	(0.098)	(0.092)
Ln Per cap exp., wave 1	0.507**	0.027	-0.005	-0.064*	-0.020	-0.014	-0.033
	(0.163)	(0.023)	(0.026)	(0.028)	(0.027)	(0.022)	(0.029)
Number of observations	1,131	1,131	1,131	1,131	1,131	1,131	1,131

Notes: OLS estimates with bootstrapped standard errors are in parentheses. *** indicates significance at 1%; ** at 5%; and, * at 10%. District dummies are included but not reported.

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

	(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
Mean hours (predicted) at baseline	-0.010	-0.003	-0.004	-0.000	0.001	0.003	0.005*
	(0.017)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Age	0.249	0.021	-0.063	0.078	0.065	0.024	0.170*
	(0.370)	(0.054)	(0.060)	(0.058)	(0.074)	(0.061)	(0.066)
Age squared	-0.004	0.000	0.002	-0.004	-0.004	-0.000	-0.005*
	(0.016)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Dad:1-6 yrs of education	-0.071	-0.024	0.068	0.030	-0.002	0.095*	-0.012
	(0.383)	(0.062)	(0.068)	(0.046)	(0.057)	(0.047)	(0.070)
Dad:7 yrs of education	1.164*	0.103	-0.001	-0.091	-0.127*	0.035	-0.112
	(0.402)	(0.062)	(0.074)	(0.059)	(0.066)	(0.046)	(0.070)
Dad:8+ yrs of education	0.950*	0.040	0.006	-0.064	-0.124	0.053	-0.119
	(0.422)	(0.069)	(0.101)	(0.069)	(0.080)	(0.057)	(0.078)
Mom:1-6 yrs of education	0.194	0.023	-0.049	-0.102*	-0.056	-0.018	-0.029
	(0.302)	(0.036)	(0.054)	(0.037)	(0.048)	(0.043)	(0.045)
Mom:7 yrs of education	0.628*	0.080*	-0.049	-0.068*	-0.030	-0.002	-0.082*
	(0.314)	(0.037)	(0.051)	(0.038)	(0.054)	(0.046)	(0.042)
Mom:8+ yrs of education	1.488	0.050	-0.239	-0.236	-0.147	-0.028	-0.035
	(1.081)	(0.106)	(0.155)	(0.145)	(0.173)	(0.121)	(0.142)
Ln Per cap exp., wave 1	0.210	-0.004	-0.004	-0.087*	-0.041	-0.005	-0.040
	(0.215)	(0.035)	(0.042)	(0.036)	(0.037)	(0.028)	(0.035)
Number of observations	640	640	640	640	640	640	640

Notes: OLS estimates with bootstrapped standard errors are in parentheses. *** indicates significance at 1%; ** at 5%; and, * at 10%. District dummies are included but not reported.

Table 8: Impact of Child Labor: 2SLS of 2004 outcomes, Males

	(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
Mean hours (predicted) at baseline	-0.055**	-0.006*	0.003	0.007*	0.001	-0.003	0.003
	(0.017)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Age	-0.067	-0.008	-0.074	0.006	-0.029	0.081	-0.024
	(0.302)	(0.061)	(0.058)	(0.060)	(0.063)	(0.064)	(0.049)
Age squared	0.014	0.002	0.003	-0.001	0.001	-0.002	0.004*
	(0.013)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Dad:1-6 yrs of education	0.491	0.063	0.004	-0.009	0.002	0.005	-0.087
	(0.399)	(0.056)	(0.065)	(0.053)	(0.064)	(0.063)	(0.058)
Dad:7 yrs of education	1.115*	0.146*	-0.041	-0.057	0.017	0.081	-0.114*
	(0.399)	(0.052)	(0.068)	(0.056)	(0.066)	(0.064)	(0.063)
Dad:8+ yrs of education	1.937**	0.228**	-0.016	-0.090	-0.041	0.088	-0.073
	(0.501)	(0.067)	(0.079)	(0.081)	(0.084)	(0.086)	(0.085)
Mom:1-6 yrs of education	0.521*	0.094*	-0.053	-0.020	-0.026	-0.127*	-0.046
	(0.267)	(0.048)	(0.045)	(0.045)	(0.057)	(0.055)	(0.043)
Mom:7 yrs of education	0.818*	0.077	-0.121*	-0.003	-0.084	-0.120*	-0.040
	(0.349)	(0.049)	(0.053)	(0.048)	(0.063)	(0.058)	(0.054)
Mom:8+ yrs of education	2.286*	0.229**	-0.264	-0.033	-0.277*	-0.200	-0.151
	(0.979)	(0.059)	(0.208)	(0.217)	(0.134)	(0.141)	(0.096)
Ln Per cap exp., wave 1	0.765***	0.053	-0.009	-0.046	-0.005	-0.013	-0.025
	(0.188)	(0.031)	(0.037)	(0.033)	(0.032)	(0.030)	(0.036)
Number of observations	673	673	673	673	673	673	673

Notes: OLS estimates with bootstrapped standard errors are in parentheses. *** indicates significance at 1%; ** at 5%; and, * at 10%. District dummies are included but not reported.