School Proximity and Child Labor
Evidence from Rural Tanzania

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Is improved school accessibility an effective policy tool for reducing child labor in developing countries? We address this question using micro data from rural Tanzania and a regression strategy that attempts to control for non-random location of households around schools as well as classical and non-classical measurement error in self-reported distance to school. Consistent with a simple model of child labor supply, but contrary to what appears to be a widespread perception, our analysis shows that school proximity leads to a rise in school attendance but no fall in child labor.

Keywords: distance to school, child labor, school enrollment.
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INTRODUCTION

Child labor is a pervasive phenomenon. The most recent global estimates from the ILO (2006) show that, as of 2004, there were around 191 million children aged 5 to 14 in economic activity worldwide, around one sixth of the child population. Sub-Saharan African children are at disproportionate risk of being classified as economically active, with approximately 26% of children working.

A major concern regarding child labor is that credit constraints or the absence of positive bequests might lead to a sub-optimal level of human capital accumulation among low income households, perpetuating an intergenerational poverty trap (Baland and Robinson, 2000; Edmonds, 2008). In addition, even if child labor does not come to the detriment of schooling (and in fact it might lead to the acquisition of skills that are valuable later in life) and despite no evidence of appreciable short-run health effects (Beegle *et al.*, 2005), concerns arise from the possibility that labor early in life might in the long-run undermine an individual's physical, psychological or cognitive development. It may also negatively impact learning capacity in adulthood. Given this, a legal ban on child labor may appear to be a viable policy option (Basu and Van, 1998). However, this might prove hard to enforce, especially when children are disproportionately working for their parents.

An alternative policy option that is often advocated is drawing children into school.[1] School attendance might be easier to monitor and, to the extent that schooling displaces child labor, policies that affect the costs of or the returns to school might prove effective in combating child labor.

A closer look at the data though suggests that this conclusion is far from warranted. The observation that a large proportion of children in several developing countries happen to be neither in school nor in work (see, for example, Biggeri *et. al.*, 2003) suggests that increased school attendance

[1] The United States Department of Labor (1998), for example**,** states that "*Universal primary education is widely recognized as one of the most effective instruments for combating child labor. [...] To be effective in eliminating child labor, education must be useful, accessible, and affordable".* ILO (2006) states that *"improving access to quality education is essential for reducing the incidence of child labour*".

might not translate into lower child labor. Similarly, the observation that a large proportion of children combine work with school also suggests that the trade-off between these two activities might be less clear-cut than suspected and generally modeled in the economic literature.

There is considerable evidence that children's school enrollment is responsive to variations in the costs of and the quality of schooling (see, for example, Banerjee *et al.*, 2007; Beegle and Burke, 2004; Duflo et al. 2008, Siddiqi and Patrinos, 1995). However, evidence on the effect of these variables on child labor is mixed (Grootaert and Patrinos, 1999). Perhaps the most convincing evidence comes from the Conditional Cash Transfers literature. Most of these programs contain an element of randomization or pseudo-randomization in treatment assignment, making their evaluation particularly credible. These policies appear to lead to a rise in schooling and a reduction in child labor (Ravallion and Wodon, 2000, for Bangladesh; Skoufias and Parker, 2001, for Mexico; Attanasio et al., 2006, for Colombia; Edmonds and Schady, 2009, for Ecuador), and with few exceptions the increase in enrollment appears larger than the fall in child labor, implying that increased enrollment comes in part from reduced inactivity. These results might suggest that child labor is relatively unresponsive to variations in the cost of schooling.

In this paper we aim to broaden our understanding of the determinants of child labor and the appropriate policy response, by concentrating on one specific dimension of the cost of attending school: travel time to school. It is widely acknowledged that school availability and accessibility impose binding constraints on children's ability to attend school in many developing countries (see, for example, Lavy, 1996; Foster and Rosenzweig, 1996; Duflo, 2001; Handa, 2002; and Filmer, 2004, for observational evidence, and, most recently, Burde and Linden, 2009, for a randomized experiment) but how this affects child labor is much less well established. While Siddiqi and Patrinos (1995), and Bhalotra and Tzannatos (2003) conclude that distance to school typically increases child labor, Grootaert and Patrinos (1999) find little supporting evidence in favor of this conclusion. A recent review of the literature by UCW (2010), the interagency (ILO-UNICEF-World Bank) research project on child labor, provides a nuanced picture of the relationship between child labor and school accessibility, with some studies finding a negative effect and other studies finding no effect. Existing studies differ markedly in the definition of accessibility, mostly relying on whether a school is present in the village or not, and, with no exception, estimates are plagued by endogeneity issues stemming from households' residential location choices, casting some doubts on causal interpretation of the estimates.

Tanzania lends itself naturally to an analysis of the effect of distance to school on children's time-use. In the last decade the country has made considerable progress in reducing child labor and enrolling children in school; this is partly attributable to high economic growth (Utz, 2007). However, as of 2000/01, more than 60% of children in rural areas were involved in some productive activity, with an average working week of around 26 hours. School attendance was far from universal, at around 67%. Additionally, more than 10% of children lived at least at 5 kilometers from the closest school, implying a daily travel time to school of at least two hours. Since it has been argued that distance is an important predictor of school attendance in Tanzania (Bommier and Lambert, 2000; Beegle and Burke, 2004), one might suspect that it could also help explain Tanzania's high level of child labor.

One advantage of our data compared to most existing survey data is that they provide distance to the closest primary school for each household in the sample, rather than village level availability. In addition, this question is asked with reference to all children, irrespective of whether they attend school or not. By exploiting the variation in accessibility to school across households in the same village, our approach offers the advantage of allowing us to separately identify the effect of school distance from unobserved village characteristics.

There are a number of empirical challenges to our analysis. Not differently from any paper that exploits residential location, it is possible that households might not be randomly located within villages. Better-off households, who presumably have a lower propensity to send their children to work, are also more likely to live closer to the administrative center of the village, where schools are typically located. This might lead to erroneously conclude that higher school distance causes lower school attendance and higher child labor. A related, though potentially less serious problem is that households who are more likely or more prone to send their children to school (and presumably less likely to send them to work) might endogenously locate nearby schools or send their children to live with relatives or acquaintances who live nearby schools.

Our empirical strategy attempts to deal with non-random assignment of households to different distances from schools by including in the regressions not only a large array of observable controls, but also distance to a large number of additional facilities. This presumably washes out unobservable dimensions of households' tastes, opportunities and constraints that affect children's time-use decisions and happen to be correlated to the household residential location. A number of falsification exercises support the validity of our identification assumption.

Because distance to school is self-reported, one second major concern pertains to measurement error and the ensuing attenuation bias of the OLS estimates. 2SLS estimates that control for classical measurement error and estimates using best- and worst-case scenario assumptions to control non-parametrically for non-classical measurement error all support our conclusion.

Our empirical analysis shows that increasing distance to school appears to lead to a fall in schooling and no appreciable rise in the probability of work. If anything, we find evidence that the incidence of child labor falls as distance to school increases, although coefficients are seldom statistically significant. This suggests that, as distance to school increases, children are less likely to combine work with school and are more likely to work only.

We rationalize this result using a simple labor supply model with child labor, schooling, and leisure. We show that making schools more accessible has an *unambiguous* positive effect on school attendance but an *ambiguous* effect on child labor. While improved school accessibility increases the incentives to attend and reduces the incentives to work among children currently out of school, it also frees up time among the inframarginal children already in school, hence increasing the incentives to engage in work among this group.

The structure of the paper is as follows. Section 1 introduces the data and presents descriptive evidence on child labor, schooling and school accessibility in rural Tanzania. Section 2 presents a stylized model of child labor and schooling. Section 3 discusses the specification and identification of the empirical model and presents the regression results. Section 4 discusses these results and concludes.

1. INSTITUTIONAL BACKGROUND AND DESCRIPTIVE EVIDENCE

Like many other sub-Saharan African countries, the Tanzanian economy is largely based on agriculture, which accounts for around 80% of employment and 60% of GDP (Utz, 2007). As of 2001, the country was one of the most populous (population of about 32 million) and poorest in Sub-Saharan Africa (annual GDP *per capita* in 2001 was on the order of US$ 540, after the Democratic Republic of Congo, Sierra Leone, Chad, Niger and Malawi, with a poverty rate of 31%).

Despite being an early starter among countries in the region in prompting universal primary education, school enrollment fell precipitously during the 1980s and 1990s. This was the result of rapidly deteriorating economic conditions, rising poverty, and the government's underinvestment in education (Al-Samarrai and Reilly, 2000; Beegle and Burke, 2004; Wedgwood, 2007), coupled with exponential population growth and low returns to education.[2] Figures from UNESCO (2005) show that gross enrollment in compulsory primary education (grades 1-7) in 2000 was on the order of 63%, down from 98% in 1980 (Wedgwood, 2007). Net enrollment was substantially lower and on the order of 49%, due to a combination of late entry, intermittent attendance, and widespread grade repetition.[3]

In order to document the incidence of child labor and school attendance in Tanzania, we use micro data from the 2000/01 Household Budget Survey (HBS). This is a large cross-sectional representative survey covering 22,178 households and 108,092 individuals in both urban and rural areas. In addition to information on housing and socioeconomic characteristics, the survey also provides information on self-reported distance and travel time to a large number of infrastructures plus information on school enrollment and work in the week preceding the survey.[4] In the analysis we restrict the sample to children aged 7-14 (corresponding to the theoretical age range for primary school) in rural areas, where school supply constraints are most likely to be binding. This gives a sample of 8,641 children in 539 villages.[5]

1.1. Children's Time-use

Table 1 reports information on time-use of Tanzanian children separately by gender. To derive the information in this table we use the response to a question about the main and secondary activities of

[2] Psacharopoulos and Patrinos (2002) report a figure for the return to primary education in Tanzania of 7.9%, well below most of the other countries in the region.

[3] This situation has changed considerably since 2000. In 2001 the Primary Education Development Programme (PEDP) was launched and school fees in primary education were abolished. Apparently in response to the abolition of school fees, between 2000 and 2003 primary enrollment increased by over 2 million pupils (Shitundu, 2005).

[4] The sampling scheme is stratified as follows. First, 1,158 Primary Sampling Units (PSUs) were chosen in order to guarantee a regional representation: about half of these PSUs were rural villages. From each of these PSUs, between 12 and 24 households were interviewed between May 2000 and June 2001. The sampling scheme guarantees a mix of low, medium and high income households in each PSU. A unique identifier allows us to identify households in the same village, although the identity of the village cannot be ascertained.

[5] We exclude domestic employees, accounting for less than 0.5% of the sample, and the few individuals with no reported gender.

the child in the week preceding the survey. These include work on the household farm, in the household business and household chores (that we jointly classify as work inside the household) and work outside the household.

Working children are defined as those reporting work either inside or outside the household as either their primary or secondary activity (or both). Around 63% of boys 71% of girls age 7-14 are in work. Children are disproportionately employed on the household farm or devoted to household chores. However, involvement in household chores is significantly higher for girls than for boys; this explains their overall higher propensity to work. Boys instead are relatively more likely than girls to be employed outside the home.

Row 4 reports school attendance. This is derived from a separate question in the survey that records if the child is currently attending school. As noted by others, although the legal entry age in school is 7, school entry is very delayed in Tanzania, with attendance rates increasing up to age 13 and falling afterwards. Several forces appear to explain low enrollment rates at early ages: supply constraints and distance to school apparently being two important factors (Mason and Khandker, 1996).

Around two thirds of both boys and girls in the sample are in school. Work in combination with school is widespread, with more than half of those in school reporting some work activity (row 5). Girls are slightly more likely than boys to combine school and to work, potentially a reflection of the lower burden that household chores and work inside the household impose on children’s time compared to market work. A non-negligible proportion of children (10-12%) also declare being idle, i.e. neither in work nor in school (row 6), although this is largely ascribable to delayed school entry rather than inactivity among teenagers. Finally, working children work on average 26 hours per week (row 9), approximately equivalent to a part-time adult job (the average work week among prime-age rural men in the HBS is 53 hours). Data (not reported) show that hours of work among children in school are approximately half that of children out of school (respectively 18 and 37 hours).

To get a sense of the constraints that school attendance impose on children's time in Tanzania, it is important to note that over the period of observation the typical primary school day was six hours and children were expected to attend seven days a week (although absenteeism, especially on Sundays, the market day, is widespread), implying that a child attending school full time would devote more than 40 hours per week to school.[6] These figures show that the long normal school day coupled with typically long working hours undoubtedly take a large toll on children's time in rural Tanzania.

1.2 School accessibility

Row 10 of Table 1 reports information on self-reported travel time to the closest primary school expressed in fractions of hours. Travel to school is on average half an hour per day in each direction. The HBS also reports self-assessed physical distance to the closest primary school. Because this variable is reported in intervals, 0-1 km., 1-2 km, etc., we transform it into a cardinal variable using the mid-points of each interval (i.e. 0.5 km, 1.5 km, etc.). Average school distance to the closest primary school in row 11 is around 2.5 kilometers.[7] The evidence in rows 10 and 11 of Table 1 implies an average speed to school of around 5 kilometers per hour, similar to what is generally estimated for an average adult on regular terrain and normal conditions. This possibly suggests that the HBS respondent

[6] Beegle and Burke (2004) using data from the Kagera region find that, despite considerable absenteeism, average weekly hours of schools are on the order of 31. The HBS 2001 also reports hours of school in the previous week but only for those who declare schooling as their primary or secondary activity. The average hours of school among these children is 39 hours and this figure is remarkably similar for those in work and those not in work. We are wary of using this variable since it appears that 7% of children currently attending school do not declare schooling as either their primary or secondary activity. These are children with stronger labor market attachment and more likely to be absent from school. Because of this, average hours of school in the HBS are likely to be overestimated.

[7] This figure is in the same ball-park as the one found in other data sets. Distance to primary school among those currently in school in the 1993 Human Resource Development Survey (HRD) is 1.8 km. In the HBS school distance among children currently in school is 2.1 km

interprets this question as referring to "normal" travel time by an adult. Travel time might be considerably larger for a child, especially a young child.[8]

The first column of Table 2 reports the cumulative distribution of the distance to school among households in the sample. 73% of children live within 3 kilometers from the closest primary school and 89% live within 5 kilometers, implying a daily travel time to school of at least two hours for more than 10% of children.

The evidence above suggests that a non negligible fraction of children are located at considerable distance to the closest school. This variation is largely ascribable to the circumstance that Tanzanian villages cover large physical areas and that households live in rather widespread radiuses around schools, rather than to the absence of schools *per se*. This is consistent with institutional evidence, as the early 1970s decentralization experience endowed most Tanzanian villages with a number of services and infrastructures, including schools (Semboja and Therkildsen, 1994).[9]

Columns 2 and 3 of Table 2 report respectively the proportion of villages with at least 25% or 75% of the population within a certain distance from the closest primary school. Consistent with the notion that all HBS villages have a school, column 2 illustrates that in virtually each village there are households living close to the primary school. For example, 81% of villages have at least 25% of the population within 2 kilometers from school.

Reading across rows, one can also see that there is substantial variation in school distance within villages. In fact, if most of the variation in school distance is between villages, figures in each row will be roughly constant. Conversely, the table shows substantial variation across columns. For

[8] Indeed, we find no association between children's age or gender and self-reported travel time, whether conditional or unconditional, on travel distance. This implies that respondents are unlikely to interpret this question as referring to the travel time taken by children in their household to reach the closest school.

[9] The HBS data do not provide direct information on whether a village has a school and since the identity of the villages is unknown, one cannot ascertain if a village has a primary school using auxiliary data sources. Mason and Khandker (1996) found that all villages in the 1993 HRD data have a primary school. The same is found by Beegle and Burke (2004) for Kagera.

example, row 1 shows that while 57% of villages have at least 25% of children living within 1 kilometer from the closest primary school, only 16% of villages have at least 75% of households within that radius. This guarantees that substantial variation in distance to school exists across households within the same village to identify the effect of school distance.

2. A MODEL OF WORK AND SCHOOL WITH TRAVEL TIME TO SCHOOL

Having ascertained that a non-negligible fraction of Tanzanian children live at considerable distance from school, we now turn to a more formal analysis of children's optimal work and schooling decisions as schools become more accessible. The model is similar in spirit to Edmonds (2008), and is reminiscent of Cogan's (1981) model of labor supply with fixed travel time to work. Accessibility here is modeled as travel time to school.

Assume that households maximize the following utility function:

$$\max_{C,E,P} U(C,P,E) \qquad s.t. \qquad C = wM + Y, \quad M + P + E(1+t) = 1, \quad E, M, P \geq 0$$

where C is consumption, P is leisure time, E is schooling, Y is income (excluding income from child labor), w is the children's wage rate, M is hours of work and t is travel time to school. We assume that the time endowment is fixed and equal to 1 and - to keep things simple - that there are no monetary costs of schooling. We return to this hypothesis later. For simplicity, we also assume that $lim_{P \to 0} U(\,.) = -\infty$, so that, at the optimum, children always consume some play time.

Children are in school if $MRS_{PE} > (1+t)$, where $MRS_{PE} = (\partial U/\partial E)/(\partial U/\partial P)$ is the marginal rate of substitution between leisure and school evaluated at $E=0$ (and $P=1-M$, $M \geq 0$). In this model, an increase in school distance acts as a rise in the price of schooling, and the probability of being in school $S=I(E>0)$ falls as t rises:

(1) $$\frac{\partial \Pr(S)}{\partial t} \leq 0$$

Children are in work $N=I(M>0)$ if $w>MRS_{PC}$, where MRS_{PC} is the marginal rate of substitution between leisure and consumption evaluated at $M=0$ (and $P=1-E(1+t)$, $E\geq 0$), i.e. the reservation wage evaluated at the optimal schooling choice. Note that, conditional on S, $\partial MRS_{PC}/\partial t \geq 0$. This is because, among children who remain in school as t rises, higher travel time comes to the detriment of leisure. Because of decreasing marginal utility of leisure, the reservation wage increases as t rises and participation falls:[10]

(2) $$\frac{\partial \Pr(N \mid S)}{\partial MRS_{PC}} \frac{\partial MRS_{PC}}{\partial t} = \frac{\partial \Pr(w > MRS_{PC} \mid S)}{\partial MRS_{PC}} \frac{\partial MRS_{PC}}{\partial t} \leq 0$$

From (1) and (2), one can sign the effect of changes in t on the probability of work:

(3) $$\frac{\partial \Pr(N)}{\partial t} \approx \frac{\partial \Pr(N \mid S)}{\partial t} \Pr(N \mid S) + [\Pr(N \mid S) - \Pr(N \mid \overline{S})] \frac{\partial \Pr(S)}{\partial t}$$

The first term picks up the effect of increased school distance on the inframarginal children, i.e. those whose attendance behavior is unaffected. This is negative. The second term picks up changes in participation among the marginal children who drop out of school as t rises. This is positive, as labor market participation is higher for those out of school than for those in school $[\Pr(N \mid \overline{S}) > \Pr(N \mid S)]$.

The sign of the left-hand side term in (3) is indeterminate: making schools more accessible has an *unambiguous* effect on school attendance but an *ambiguous* effect on child labor. On the one hand, among those who would have attended school anyway, more time is available and hence work becomes a more appealing option. These children will be more likely to work while in school. On the other hand, by encouraging school attendance, travel to school takes up time from productive activities, hence discouraging work.

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[10] Clearly, among individuals out of school, labor market participation is unaffected by changes in t, i.e. $\partial \Pr(N|\overline{S})/\partial t = 0$

The model clearly illustrates that, if, as often assumed in the theoretical literature, children do not combine work with school, $\Pr(N|S)=0$, a fall in travel time to school will unequivocally decrease child labor. However, precisely because in many developing countries school appears not to be incompatible with some amount of work (and indeed this is true for 40% of Tanzanian children), the effect of accessibility is ambiguous. The model also illustrates that, if the probability of work while out of school $\Pr(N \mid \overline{S})$ is low, child labor might not necessarily decrease as distance to school falls and enrollment rises, as the latter might simply come from reduced inactivity, a point made by many others, including Ravallion and Wodon (2000).

The model ignores monetary costs of schooling. It is easy to see, though, that these will reinforce the negative effect of school distance on child labor. If more children are drawn into school when the latter becomes more accessible, more children might have to work in order to support their own or their siblings' school attendance.

3. SCHOOL DISTANCE AND CHILD LABOR

3.1 Preliminary evidence

Before presenting a formal empirical analysis, we start by presenting some suggestive evidence of the effect of school distance on attendance and child labor. Table 3 presents the frequency distribution for the main reason given for children not attending school in the reference week. This question is asked in the HBS with reference to all children not in school. The most important reason provided for lack of attendance is the monetary cost of school (13% of children), together with lack of interest or lack of perceived usefulness (11%). Around 8% of children appear not to attend as they are involved in work, implying that work possibly displaces schooling. Interestingly, though, around 5% of children appear not to attend due to the school being too far.[11]

The bottom part of the table refers to the main reason provided by the adult respondent for children currently being in work. Although this question is not available in the HBS, this is asked in the 2001 Tanzania UNICEF Multiple Indicator Cluster Survey (MICS). Almost 90% of parents declare that their children work in order to either supplement household income or to provide help in the family enterprise or business. Interestingly, only a negligible fraction (half a percentage point) of parents report that their children work due to schools being too far from the place of residence.

Although clearly some caution must be exerted in drawing inference based on subjective responses, these figures appear to suggest that school distance is not perceived as a major determinant of children's work in Tanzania. Work is apparently driven by poverty and it might displace schooling. We now turn to a more formal analysis of the effect of school distance on school attendance.

3.2 Basic Regression Results

In the rest of this section we present the results of a number of regressions of children's time-use on distance to primary school. Because we have no credible instrument for assignment of children to schools, we attempt to recover the effect of school distance on children's time-use by controlling for observable household and unobservable village characteristics. We discuss later in the paper potential sources of bias in the estimates and we present a number of checks for our results.

We regress children's time-use (*Y*: work, school, etc.) on the household's self-reported travel distance to the nearest primary school measured in kilometers (*distance*) plus a set of controls (*X*):

(4) $Y_{it} = \beta_0 + \beta_1\, distance + X_i'\, \beta_2 + u_i$

[11] This question is strongly correlated with the household's self-reported distance to school. Average distance to school among those currently out of school who report distance as being the major constrains is 6.41 km versus 2.46 km among other children out of school.

where u is an error term.

We use physical distance rather than travel time as a measure of school accessibility. We do so because, although travel distance is potentially not free of measurement error (the consequences of which we discuss below), we are particularly concerned that travel time might be endogenous to school attendance. Those who have a stronger ability or desire to send their children to school might also be the ones who are able to cover the same distance in a shorter time via faster modes of transport.

Table 4 reports OLS estimates of equation (4), where coefficients are multiplied by a factor of 100. Each row refers to a different variable and each column to a different specification. All specifications control for dummies for child's age, gender and interactions of the two, dummies for the child's relationship to the household head (spouse, child of head, child of spouse, grandchild, and other relative) plus month of interview dummies. By including month of interview dummies we control for the potential seasonality in children's work and schooling linked to the harvest season and the school holiday period (mid June to early July and early December to mid January). Standard errors are clustered at the household level.

Column 1, row 1 illustrates that one extra kilometer to the closest primary school is associated to a rise in the probability of work of 0.42 p.p. This is largely ascribable to a fall in the probability of combining work and school and an even bigger rise in the probability of work with no school (rows 3 and 4). Higher distance to school appears also to be associated to lower school attendance: the estimated coefficient is on the order of -1.67 p.p.

In column 2, where we additionally control for a very large array of arguably exogenous household characteristics (see table for details), the coefficient on child labor falls (that is now 0.17 and statistically insignificant) and the coefficient on school increases (that is now -0.81 as opposed to -1.67 in column 1). This is evidence that more affluent households live closer to schools and that their children are less likely to work and are more likely to attend school. This is further confirmed in column 3 where we include the household's self-reported distance to a large array of other infrastructures and services.[12] The concern is that proximity to school proxies for the household socioeconomic status that is only partially accounted for by observed household characteristics: poorer households might live further away from the administrative center of the village where schools tend to be located. Indeed, studies have shown that household location is correlated to children's use of time.[13] Point estimates fall further in absolute value: for example, the coefficient on work is now negative and small but statistically insignificant while the coefficient on schooling is negative (-0.48) and significant at conventional levels. Indeed, households living closer to schools also live closer to other facilities, and closeness to facilities other than schools is systematically associated with lower child labor and higher schooling.

To address the concern that omitted village characteristics might affect our estimates, we finally include village fixed effects in our regression. These regressions offer the advantage of comparing children in the same labor market, so they wash out differential returns to education or work opportunities that are specific to each village. Compared to the corresponding estimates in column 3, the inclusion of village fixed effects (column 4) tends to lower the point estimates in the child labor equation while the reverse happens in the schooling equation. This suggests some role for unobserved village heterogeneity in explaining work and school decisions.

Column 4 shows that child labor is overall unaffected by school distance: the point estimate is negative (-0.27) but statistically insignificant. Hours of work also appear not to vary with school distance. Row 3 shows that children who live further away from school tend to be less likely to

[12] These are: Police Station, Traditional birth attendant, Religious center, Primary court, Hospital, Place for water, Place for wood, Market, Shop, Health center, Secondary school, Bank, Post office, Transport, Mill, Community center, and Cooperative.
[13] Fafchamps and Wahba (2006), for example, show that proximity to urban areas is negatively correlated to the incidence of child labor, although the probability of market work is higher for children living nearby cities.

combine work and school (coefficient -0.52). This is associated with an almost equal fall in schooling on the order of 0.36 p.p. We also find no statistically significant variation in inactivity, school only, or work only.

3.3 Non linear effects

In Table 5 we investigate whether there are non-linearities in the effect of distance on children's time-use. We report regression coefficients from a specification that includes dummies for households at different distances (1-2 km, 2-3 km 3-4 km, 4-5 km, and more than 5 km, with less than one kilometer being the omitted category). We see clear patterns in the probability of attending school as distance increases: there is a clear negative gradient and the marginal effects decrease with distance. Being between 1 to 2 kilometers from school relative to being within 1 kilometer decreases school attendance by about 5 p.p., while being at between 4 and 5 kilometers relative to between 3 and 4 kilometers lowers the probability of school attendance by only around 0.5 p.p. Similar to what we found in Table 4, the coefficients in the work and inactivity regressions are small, showing no clear pattern, and are statistically insignificant. The only remarkable difference with respect to Table 4, column 4, is that now the coefficients in the work only regression become positive and significant, and display an increasing pattern as distance increases. This completes the picture in Table 4: higher school distance pushes children away from school in combination with work towards work only. Although, consistent with what is postulated in the model and with findings elsewhere in the literature, we find that school distance affects school attendance, but we find no evidence of this affecting child labor.

3.4 Heterogeneous effects

The remaining columns of Table 4 report results separated by age and gender. We revert to most saturated specification as in column 4 of Table 4. Distance to school postpones school entry, lowering school attendance among young children (coefficient: -0.59), but not among older children (coefficient: 0.01). Increased school distance appears to push older children who are in school to drop out of the labor market. Essentially, child labor falls but not significantly so (-0.37).

These findings shed some additional light on the role of school distance on child labor. Distance to school imposes a binding constraint on children's school attendance (the second term of the decomposition in (3)) only at early ages, when walking to school might be particularly arduous and even hazardous. However, young children are unlikely to be engaged in work and the effect of a greater distance to school on child labor is negligible. For older children, greater school distance does not significantly affect school attendance but only the propensity to combine work with school, which if anything, falls at higher distance from school (the first term of the decomposition in (3)).

Turning to differences across boys and girls in columns 7 and 8 of Table 4, we find no statistical differences in the effect of school distance on school attendance between gender groups. One significant difference between girls and boys is that, among those combining work with school, the latter tend to drop out of school and devote exclusively to work as distance increases, while the former tend to drop out of the labor market and to remain in school. Potentially, this reflects the circumstance that girls' labor market returns are low and the incentives to engage in productive activities are hence reduced compared to boys.

We have also run separate regressions for work inside and outside the household (results not reported). The findings are very similar: there appears to be no clear pattern of substitution between work inside and outside the household as children drop out of school as a result of increasing school distance. Results by income level (also not reported) show that, as expected, most significant effects are found for children in poorer households, although, even for these children, we find no evidence of child labor increasing as distance from school increases.

3.5 Potential threat to the consistency of the OLS estimates: falsification tests

The OLS estimates in Tables 4 and 5 attempt to control for non-random assignment of children to school through the inclusion of a large array of household controls, distances to other infrastructures, and village fixed effects. It is reassuring that, consistent with what others have found in the literature, school distance appears to impose a binding constraint on children's school attendance. Despite this, we find no statistically significant effect of school distance on child labor. The inclusion of observable household and unobservable village controls shows that OLS estimates are upward biased, potentially suggesting that unobserved factors might further lower the point estimate in row 1 of Table 4.

As a way to check the validity of the identification assumption, we present a number of falsification tests. Table 6 reports regressions of log household per capita income and hours of work for the head and his spouse on the same specification as in Table 4, column 4. We find no evidence that, along any of these dimensions (and conditional on a large array of additional covariates), households living further away from school behave differently from those living nearby. These finding also appear to rule out the possibility that children living further away from schools happen to work less than children close-by due to limited work opportunities, a competing explanation for the results in Table 4 that child labor declines (although not significantly so) as distance to school increases. There is little evidence of school distance being correlated to other meaningful economic outcomes, lending some support to the findings in the previous sections.

A related concern is that households or children might endogenously locate near schools. In particular, if those who are more likely to attend school and less likely to work also decide to locate closer to schools, then one would again underestimate the coefficient in the child labor equation, while the opposite will happen for the coefficient in the schooling equation. A concern is that, even if households do not move, children might be fostered by related or unrelated households living near schools in order to allow them to attend, a practice that is widespread throughout sub-Saharan Africa, including Tanzania, at least for secondary school children.[14] In row 4 of Table 6 we report a regression where the dependent variable equals one if the household has a child of primary school age (7 to 14) and zero otherwise. We use all households in the sample to run this regression. Again, we find no evidence of distance to school being correlated to the presence of children ages 7-14 in the household, whether they are the children of the head of the household or not. Endogenous mobility is unlikely to affect our estimates.

3.6 Classical measurement error

A second concern regards measurement error in the distance measure. Self-reported distance measures are potentially error-ridden measures of accessibility (see, for example, Gibson and McKenzie, 2007), leading to an attenuation bias in the estimates. This might explain the predominance of zero effects found for work. The measurement error problem is likely to be exacerbated by the inclusion of village fixed effects. If anything, classical measurement error should lead to estimates of the effect of distance on child labor that are biased towards zero.

In order to account for classical measurement error, we instrument travel distance to school using the household reported travel time to the nearest school. Although travel time might also be an error ridden measure of school accessibility, 2SLS should purge the estimates of classical measurement error in so far as the measurement errors in these two variables are uncorrelated.

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[14] Ainsworth et al. (2005) estimate that about 16% of all households have a foster child while our data show that around 9% of children in our sample are classified as other relatives of the household head (this excludes children or grandchildren of the head or the spouse).

The first stage estimates (not reported) show that the average speed to school is around 4.3 kilometers per hour, in line with the results shown in Table 1 (results with the inclusion of fixed effects are slightly lower than simple OLS estimates: speed to school is higher in villages where households live in more widespread areas). The estimate is very precise, with a t-statistic of around 8. Table 6, column 1 reports 2SLS estimates of equation (4). These are similar to, though less precise than, the OLS estimates in Table 4, column 4, with work being unaffected by distance to school.

3.7 Non-classical measurement error

Potentially, a more serious concern is non-classical measurement error, i.e. the circumstance that measurement error is correlated to actual distance. One possibility is that households whose children are out of school tend to over-report distance to school. In this case, reported distance to school will be negatively correlated to school attendance. This might be due, for example, to some misinformed households overestimating distance to school and, hence, being less likely to send their children to school. Households with no children in school might also have less precise information about the distance to the closest school or they might over-report distance to school as a way to rationalize their decision not to enroll their children to either themselves or the interviewer. To the extent that school and work are negatively correlated, this will imply that working children are in fact closer to schools than reported, suggesting that the coefficient in the child labor regression will be overestimated. This would presumably reinforce the main conclusion of the paper, i.e. that lower school distance does not lead to a fall in child labor.

To check for this, we have assigned to each household with at least one child out of school the minimum distance among the households with all children currently in school in its village of residence. Estimates that use this modified regressor, derived under the worst-case scenario of negative selection, should provide a lower bound for the actual effect in the child labor regression. These regressions are reported in column 2 of Table 7. As expected, the worst-case scenario coefficient (-0.940) is well below the coefficient in Table 4, column 4, suggesting that negative selection is not an issue for the main conclusion of this paper.

Perhaps a more worrisome source of non-classical measurement error stems from the circumstance that those in school report distance to the school they actually attend rather than the closest school. If there is more than one school in the village or some children attend schools in other villages, the opposite bias might arise, with the coefficient in the child labor regression being downward biased. In this case, non-classical measurement error in distance to school is negatively correlated to child labor. We have used a similar procedure to account for this source of selection. For each household with at least one child in school, we have replaced reported school distance with the maximum distance among households with no children in school in its village of residence. Results are reported in column 3 of Table 7. The upper bound estimate for the coefficient in the child labor regression in the case of perfect positive selection is 0.068 and statistically insignificant.

As additional robustness checks (not reported) we have re-imputed schooling for those 72 children that fail to report it. We are particularly concerned that these might be children at higher distance and with lower probability of school attendance and higher probability of work. We have again computed worst- and best-case scenario selection-adjusted estimates of the effect of school distance on children’s time use. Results, perhaps unsurprisingly given that the percentage of selected observations is rather small, are essentially unchanged. We come to similar conclusions if we re-impute distance for the 20 observations that fail to report it. Again we impute the lowest and the highest distance in their village or residence to compute bounds.

4. SUMMARY AND CONCLUSIONS

This paper investigates how distance to school affects child labor using data from rural Tanzania. While our theoretical analysis echoes Ravallion and Wodon's (2000) point that increased school enrollment does not necessarily lead to an equal fall in child labor, we go one step further, by arguing that increases in enrollment induced by improved school accessibility might, as an unwanted consequence, lead to a rise in child labor.

Using data from Tanzania in 2000/01, we show that, while a one kilometer increase in distance to school is on average associated to a fall of around 0.4 p.p. in the probability of school attendance, there is no significant effect on child labor at either the intensive or extensive margin. Our results are unchanged when we control for selection of households around schools and potential measurement error. Our results are consistent with Basu and Van's (1998) luxury axiom, whereby children work if and only if the household needs their work to reach a subsistence consumption level and work is overall inelastic to changes in the cost of schooling.

A few remarks are worth mentioning in closing. First, although in the paper we ascribe the negative coefficient on school distance in the school attendance regression to physical accessibility, this coefficient might pick up additional mechanisms. For example, parents might be better informed about the returns to education or the quality of schooling if schools are nearby, or they might be more likely to be involved in the school activities, and these might increase their stakes in their children's education. Although we have no precise way of identifying what mechanisms explain the negative coefficient in the schooling regression, our results on the effect of school distance on child labor stand, namely that this does not affect child labor, whether through improved access or other channels.

Second, it is important to remark that our results exploit the variation in distance to school across households in the same village. Despite Tanzanian villages being quite widespread, these estimates are only able to identify the effect of marginal changes in distance to school among households relatively close to school: almost 90% of households in the sample live within a radius of 5 kilometers from the closest school. Our results might not necessarily extrapolate to households living at higher distance or, most importantly, to increased availability of schools in rural areas of developing countries that completely lack them. It is likely that such increased availability will lead to an unambiguous fall in child labor.

By the same token, the external validity of our estimates is limited by the institutional features of the Tanzanian school system. Because, at least during the period of observation, the school day was 6 hour and the average work day was (on a six day basis) 4 hours, higher school distance might impose binding constraints on children's decision to work while in school. It is possible that, in other contexts, improved school accessibility has an effect on school attendance but it does not significantly affect the labor supply decisions of inframarginal children already in school and that it leads overall to a fall in child in labor.

References

Ainsworth, Martha, Kathleen Beegle and Koda Godlike (2005), 'The Impact of Adult Mortality and Parental Deaths on Schooling in North-Western Tanzania', *Journal of Development Studies*, 41(3): 412-439, 2005.

Al-Samarrai, Samer, and Barry Reilly (2000), 'Urban and Rural Differences in Primary School Attendance: An Empirical Study for Tanzania', *Journal of African Economies*, Vol. 9, No. 4, December 2000.

Attanasio Orazio, Emla Fitzsimons, Ana Gomez, Diana Lopez, Costas Meghir and Alice Mesnard (2006), 'Child Education And Work Choices in the Presence of a Conditional Cash Transfer Programme in Rural Colombia', forthcoming, *Economic Development and Cultural Change*.

Baland, Jean Marie and James Robinson (2000), 'Is Child Labor Inefficient?', *Journal of Political Economy*, 108(4): 663-679, 2000.

Banerjee, Abhijit, Shawn Cole, Esther Duflo and Leigh Linden (2005), 'Remedying Education: Evidence from Two Randomized Experiments in India', *The Quarterly Journal of Economics*, vol. 122(3), pages 1235-1264, 08.

Basu, Kaushik and Pham Hoang Van (1998), 'The Economics of Child Labor', *American Economic Review*, 88(3): 412-427, 1998.

Beegle, Kathleen and K. Burke (2004), 'Why Children Aren't Attending School: the Case of Northwestern Tanzania', *Journal of African Economies*, 13(2): 333-355, 2004.

Beegle, Kathleen, Rajeev Dehejia and Roberta Gatti (2005), 'Why Should We Care About Child Labor? The Returns to Schooling vs. the Returns to Experience in Vietnam', forthcoming, *The Journal of Human Resources*.

Bhalotra, Sonia and Zafiris Tzannatos (2003), 'Child Labor: What Have We Learnt?', *Social Protection Discussion Paper Series*, No. 0317, World Bank, September 2003.

Biggeri, Mario, Lorenzo Guarcello, Scott Lyon and Furio Camillo Rosati (2003), "The puzzle of idle children: neither in school nor performing economic activity: Evidence from six countries', *UCW working paper*, 2003.

Bommier, Antoine and Sylvie Lambert (2000), 'Education Demand and Age at School Enrollment in Tanzania', *Journal of Human Resources*, 35(1):177-203, 2000.

Burde, Dana and Leigh L. Linden (2009), *The Effect of Proximate Schools: A Randomized Controlled Trial in Afghanistan*, mimeo, Columbia University.

Cigno, Alessandro and Furio Camillo Rosati (2005), *The Economics of Child Labor*, Oxford University Press, 2005.

Cogan, Joe (1981), 'Labor Supply and Fixed Costs', *Econometrica*, 49(4): 945-963, 1981.

Duflo, Esther (2001), 'Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment', *American Economic Review*, 91(4): 795-813, 2001.

Duflo, Esther, Hanna Rema and Stephen R. Ryan (2008), *Monitoring Works: Getting Teachers to Come to School*, mimeo, MIT, 2008.

Edmonds, Eric (2005), 'Does Child Labor Decline with Improving Economic Status?', *The Journal of Human Resources*, 40(1): 77-99, 2005.

Edmonds, Eric (2008), 'Child Labor', *Handbook of Development Economics Volume 4*: T.P. Shultz and J. Strauss, eds., 2008.

Edmonds Eric and Norbert Schady (2009), *Poverty Alleviation and Child Labor*, mimeo, Department of Economics, Dartmouth College.

Filmer, Deon (2004) 'If You Build It, Will They Come? School Availability and School Enrollment in 21 Poor Countries', *World Bank Policy Research Working Paper*, 3340, June 2004.

Foster, Andrew D., and Mark R. Rosenzweig (1996), 'Technical Change and Human Capital Returns and Investments: Evidence from the Green Revolution', *American Economic Review*, 86(4): 931-953.

Gibson John, and David McKenzie (2007), 'Using Global Positioning Systems in Household Surveys for Better Economics and Better Policy', *The World Bank Research Observer*, 22, 217-241.

Grootaert Christiaan and Harry Anthony Patrinos (1999), 'Policies to reduce child labor', in Grootaert Christiaan and Harry Anthony Patrinos (eds.), *The Policy Analysis of Child Labor*, Palgrave Macmillan.

Handa, Sudhanshu (2002). 'Raising Primary School Enrolment in Developing Countries: The Relative Importance of Supply and Demand, *Journal of Development Economics*, 69(1): 103-128.

ILO (2006), *The end of child labour: Within reach*, Geneva, 2006.

Mason, Andrew D. and Shahidur R. Khandker (1996), 'The Determinants of Enrollment and Late Starting Decisions in Tanzania' *HCD Working Paper*. Poverty and Social Policy Department. The World Bank.

Psacharopoulos, George and Harry Anthony Patrinos, (2002), 'Returns to investment in education : a further update', *Policy Research Working Paper Series*, 2881, The World Bank.

Ravallion, Martin and Quentin Wodon (2000), 'Does Child Labor Displace Schooling? Evidence on Behavioural Responses to an Enrollment Subsidy,' *Economic Journal*, vol. 110(462), C158-C175, 2000.

Semboja Joseph and Ole Therkildsen (1994), 'Decentralization, Participation and Spatial Equity in Rural Tanzania: A comment', *World Development*, 22, 5, 807-810.

Shitundu, Joseph M. (2005), 'Youth Employment Inventory of Existing Policies and Programmes in Tanzania', mimeo, *World Bank Social Protection Unit*, 2005.

Siddiqui, F. and Patrinos, H.A. (1995), 'Child Labor Issues, Causes and Interventions', *World Bank HR and Operations Policy working paper*, 1995.

UNESCO (2005), Global Monitoring Report, 2003-2004.

UCW (2010), *Joining forces against child labour, Inter-agency report for The Hague global child labour conference of 2010*, Rome, 2010.

U.S. Department of Labor, Bureau of International Labor Affairs (1998), By the Sweat & Toil of Children (Volume V) Efforts to Eliminate Child Labor, Washington DC, 1998.

Wedgwood Ruth (2007), 'Education and poverty reduction in Tanzania', *International Journal of Educational Development*, 27, Issue 4, July 2007, 383-396.

Utz Robert J. (2007), *Tanzania: Sustaining and Sharing Economic Growth*, World Bank, Washington DC.

Table 1
Children's Time-use: Descriptive Statistics

	(1) Boys	(2) Girls
1. Work	0.632	0.707
2. Work outside household	0.187	0.122
3. Work inside households	0.485	0.647
4. School	0.632	0.660
5. Work & school	0.389	0.464
6. Idle	0.122	0.094
7. Work only	0.246	0.246
8. School only	0.234	0.186
9. Hours work	26.274	25.726
10. Time to school (hours)	0.503	0.472
11. Distance to school (km)	2.534	2.485

Notes. The table reports time-use patterns of boys and girls age 7-14 in rural Tanzania. Number of observations 8,641. Source HBS, 2000/01.

Table 2
Distribution of Distance to School

	(1)	(2)	(3)
	% households within given distance from school	% of villages with at least the following proportion of the population within given distance from school	
km		25%	75%
1	0.35	0.57	0.16
2	0.58	0.81	0.40
3	0.73	0.92	0.59
4	0.84	0.97	0.76
5	0.89	0.99	0.85

Notes. The table reports the cumulative frequency distribution of distance to the closest primary school. Column 1 reports the distribution across all households in the sample. Columns 2 and 3 report respectively the proportion of villages with at least 25% and 75% of households within each distance. Source: 2000/01 HBS.

Table 3
Self-reported reasons for working and not attending school

	(1) Boys	(2) Girls
Not in school		
School too expensive	12.62	14.39
School Useless/uninteresting	11.68	11.37
Child working	8.20	7.44
School too far	4.66	4.56
Child too old	4.23	4.42
Child ill/pregnant	3.36	4.28
Child failed exam	0.25	0.70
Child got married	0.06	0.14
Other	54.94	52.70
Work		
To supplement household income	43.22	41.78
To assist in household enterprise	45.96	45.53
Education program not suitable	2.05	2.29
School too far	0.42	0.54
Other	8.36	9.86

Notes. The top part of the table reports the distribution of the main reason for children not attending school as reported by the adult respondent. Figures refer to children aged 7-14 in rural Tanzania. Number of observations 3,034. Source HBS 2000/01. The bottom part of the table reports the distribution of the main reason for children working as reported by the adult respondent. Figures refer to children aged 7-14 in rural Tanzania. Number of observations 5,036. Source MICS, Tanzania 2001.

Table 4
Distance to Primary School and Children's Time-use

Dependent variable	Pooled				By Age		By gender	
					7-10	11-14	boys	girls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Work	0.425***	0.176	-0.129	-0.270	-0.207	-0.374	-0.095	-0.492*
	(0.140)	(0.224)	(0.229)	(0.226)	(0.267)	(0.248)	(0.225)	(0.263)
2. School	-1.670***	-0.813***	-0.484***	-0.365**	-0.593***	0.011	-0.380*	-0.342
	(0.134)	(0.161)	(0.159)	(0.168)	(0.176)	(0.291)	(0.199)	(0.228)
3. Work and school	-1.101***	-0.629***	-0.546***	-0.519***	-0.569***	-0.435*	-0.490***	-0.553**
	(0.142)	(0.161)	(0.183)	(0.169)	(0.177)	(0.254)	(0.167)	(0.255)
4. Work only	1.526***	0.806***	0.417*	0.249	0.362	0.061	0.395*	0.061
	(0.127)	(0.233)	(0.231)	(0.231)	(0.254)	(0.279)	(0.220)	(0.274)
5. School only	-0.569***	-0.183	0.062	0.153	-0.024	0.447*	0.109	0.211
	(0.125)	(0.136)	(0.138)	(0.156)	(0.165)	(0.256)	(0.199)	(0.186)
6. Neither school	0.145	0.007	0.067	0.117	0.231	-0.073	-0.014	0.281
nor work	(0.089)	(0.148)	(0.167)	(0.140)	(0.215)	(0.114)	(0.123)	(0.223)
7. Hours of work	0.440***	0.200*	0.014	-0.013	-0.017	-0.006	0.040	-0.080
(0 if not in work)	(0.059)	(0.105)	(0.096)	(0.096)	(0.092)	(0.153)	(0.093)	(0.124)
HH controls	no	yes	yes	yes	yes	yes	yes	yes
Distance controls	no	no	yes	yes	yes	yes	yes	yes
Village FE	no	no	no	yes	yes	yes	yes	yes

Notes. The table reports the OLS coefficient on distance to primary school (multiplied by 100). Each cell of the table refers to a separate regression. Rows refer to different dependent variables while columns to different specifications. All regressions control for age dummies interacted with a gender dummy, dummies for relationship to the household head (spouse, child of head, child of spouse, grandchild, other relative) and dummies for month of observations. Household controls include household head's and spouse's sex, age and age squared, head's number of completed school grades, farming land owned, number of cattle and sheep owned, number of meals per day, whether the household had fewer than usual number of meals in the last 30 days, dummies for the number of individuals in the household in different age cells (0, 1-6,7-11, 12-14, 15-20, 21-45, 46-60, 61 or over) dummies for whether the house has foundations, material of the roof (grass or leaves, mud and grass, cement, metal sheets, asbestos, tiles, other) type of floor (earth, concrete, other), type of walls (poles, poles and mud, mud only, mud bricks, baked bricks, concrete, other), type of toilet (no toilet, flush toilet, latrine, other), type of water access (private in house, private outside house, neighbor, in community, rain catchment, public well, private well, spring, river, dam or lake, other), whether the house has electricity and number of rooms. We also include dummies for missing covariates. Distance controls include primary school, market place, shop, health center, traditional birth attendant, hospital, cooperative society, mill, secondary school, bank, post office, police, primary court, religious center, public transport, community center, place where the household gets water during the dry season and place where the household gets wood for fire. Columns 5 and 6 allow the coefficient on school distance to vary across age groups. Columns 7 and 8 allow the coefficient on school distance to vary across gender groups. Number of observations 8,641. Standard errors clustered by household in brackets. ***: significant at 1%, ** significant at 5%, *: significant at 10%.

Table 5
Non Linear effects

Dependent variable	(1)	(2)	(3)	(4)	(5)
	+ 1-2 `	+ 2-3 km	+ 3-4 km	+ 4-5 km	+ >5 km
1. Work	1.987	-1.827	1.667	1.499	-0.860
	(1.608)	(1.948)	(2.220)	(2.754)	(2.639)
2. School	-5.045***	-5.548***	-6.204***	-6.496**	-9.779***
	(1.416)	(1.794)	(2.123)	(2.895)	(2.677)
3. Work and school	-2.767*	-5.993***	-5.450**	-6.386**	-11.388***
	(1.655)	(1.996)	(2.209)	(3.016)	(2.788)
4. Work only	4.754***	4.166**	7.117***	7.884***	10.529***
	(1.354)	(1.748)	(2.024)	(2.839)	(2.633)
5. School only	-2.278	0.446	-0.754	-0.111	1.609
	(1.452)	(1.823)	(2.027)	(2.582)	(2.415)
6. Neither school nor work	0.291	1.382	-0.912	-1.388	-0.750
	(0.994)	(1.258)	(1.410)	(1.830)	(1.698)

Notes. The table reports similar specifications to those in Table 4, column 4. Each row refers to a separate specification. See also footnotes to Table 4.

Table 6
Falsification tests

Dependent variable	
1. Household head hours of work	-0.110
	(0.110)
2. Household head's spouse hours of work	0.055
	(0.126)
3. Log Household per capita income	-0.005
	(0.006)
4. Children age 7-14	-0.024
	(0.144)

Notes. The table reports similar specifications to those in Table 4, column 4. Hours of work include zeros for non-working individuals. Household per capita income excludes income from child labor. The depended variable in row 4 is a dummy for households with children in the age range 7-14. See also notes to Table 4.

Table 7
Controlling for Measurement Error

Dependent variable	(1)	(2)	(3)
	2SLS	School distance endogenous to school attendance	
		perfect negative selection	perfect positive selection
1. Work	-0.266	-0.940***	0.068
	(0.343)	(0.212)	(0.214)

Notes. The table reports similar specifications to those in Table 4, column 4. Column 1 reports 2SLS estimates where distance to school is instrumented by self-reported travel time to school. Columns 2 and 3 report worst-case scenario perfect positive and negative selection in distance to school. See text for details. See also notes to Table 4.