Estimating the Impacts of Child Labor on Schooling in Tanzania

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Abstract

Research that looks at the impacts of child labor on schooling proposes multiple ways in which the causality between schooling status (enrollment, interrupted schooling, and grade for age minus grade) and hours worked can be disentangled. While panel data methods are preferred to cross-sectional methods, there is still much difficulty in inferring causality even with panel data methods. This paper analyzes the problems of inferring causality associated with the different cross-sectional and panel estimation methods using household data from Tanzania. The results show that a child level fixed effects framework that utilizes an instrumental variable approach has the most promise. Nonetheless, this model is not without limitations, especially in the face of weak instruments.

I. Introduction

Human capital is one of the main drivers of economic development (Barro, 2001). One main stage to the human capital accumulation process is primary school education (Becker, 2009). However, families, especially in developing countries, may have to compromise between sending the child to school versus having him/her work in order to satisfy immediate consumption needs. This tradeoff is especially pronounced for the moderately poor households that rely heavily on subsistence farming.

One of the major components of the International Labor Organization's (ILO) definition of child labor is whether the work negatively affects children's schooling through any combination of the following: depriving the child of the opportunity to attend school, forcing the child to leave or dropout of school early, and requiring the child to juggle school along with heavy work. Given the ILO's definition, there is no specification of hours of work and what the difficulty of work has to be in order to be defined as heavy work. The reader should keep this general definition in mind throughout the paper. The ILO definition of child labor provides empiricists greater flexibility in defining child labor. I provide my empirical definition of child work in part III.

The identification of the impacts of work on primary education is confounded by the endogeneity between hours worked and the education status of the child: do children work more hours because they have low education or do they have low education because they work more hours? There are also simultaneity concerns when analyzing the impacts of child labor on schooling status, where hours of work are jointly determined with schooling status. In the same line of logic, a researcher cannot ascertain when the decision to change the enrollment status of the child occurred: the enrollment status at one time period may be due to events that occurred in between periods. Observed estimates may, therefore, be due to reverse causality.

While panel data methods are more preferred than cross-sectional methods, the problems of endogeneity and reverse causality still remain. This paper analyzes the challenge of endogeneity, more specifically simultaneity and reverse causality, through analyses of how different econometric specifications affect the soundness of results. The different econometric methods include: 1) the instrumental variable approach, 2) child level fixed effects, 3) child level fixed effects with instrumental variables, and 4) household level fixed effects, which is comparable to observing differences in siblings. Using farm household level data from Tanzania, I find a significant impact of work on the likelihood of stopping school (momentarily or permanently) and enrollment. Children are also more likely to fall behind in grade level with increased levels of work. In addition, I find that a child level fixed effects with instruments is the most preferred model as long as there is a strong instrument for hours worked. Using average rainfall deviations as an instrument for child labor, I find that the proposed impacts of child labor on schooling decisions are not due to the increase in hours necessarily, but the fact that regions which experience higher on average rainfall are also likely to have more affluent communities. This positive deviation in rainfall from the long-run average in rural villages, in turn increases the returns to education, as well as the returns to work.

In the next section, I provide a more detailed overview of the literature. In section III, I outline the background information, describe the data, provide basic descriptive statistics of the sample, and describe the variables of interest. The empirical models and the identification strategy are outlined in section IV. In section V, the results from the different estimation specifications are explained followed by the sensitivity analyses in section VI. Concluding comments follow in section VII.

II. Literature Review

Edmonds (2008) sets up a simple model of child time allocation. The implication of the model is that the parents make the schooling, leisure, and labor decisions of the child jointly. In other words, choices of attendance in school, play, and work depend on the shadow value of the child's time, which is affected by how the three items interact. This interaction is the key issue with any causal estimation of child labor on schooling. One must be able to quantify or assume certain things about the shadow value of the child's time in order to assess the causal impact of child labor on schooling.

Edmonds (2008) explains that there have typically been two distinct approaches when estimating the causal impacts of work on schooling. Researchers either rely on 1) legal variation in schooling requirements put in place by the government or, 2) make certain modeling assumptions about the interaction between child labor and schooling. Studies that use the first approach are less likely to satisfy the exclusion restriction (see Bezerra, Kassouf, and Arends-Kuenning, 2007; Emerson and Souza, 2004). The second approach is much more common and allows one to differentiate labor effects from child and household characteristics that could be correlated with the number of hours worked. The instrumental variable approach is under the umbrella of the modeling assumption approaches. In these studies, one assumes that certain factors affect whether a child works without affecting the child's schooling outcomes. When there is a valid instrument, which satisfies this exclusion restriction and is able to resolve some of the endogeneity between child labor and schooling, one is able to exploit variation in child labor to identify causality on schooling outcomes.

There are many studies that use the IV approach. Boozer and Suri (2001) use regional variations of rainfall to account for some of the endogeneity of child labor. They conclude that a one hour increase in child labor leads to a 0.38 hour decrease in contemporaneous schooling. Beegle, Dehejia, and Gatti (2008) use standardized rainfall deviations and crop shocks as instruments for child work hours to find significant impacts on completed grade levels and an increase in the likelihood of farming for boys and a decrease in the age of marriage for girls. However, the exclusion of rainfall from schooling decisions may be in question for Boozer and Suri (2001) and Beegle et al. (2008). High rainfall areas may already be affluent, which in turn means they are communities with better quality schools and therefore have higher marginal economic return to school and child work. The higher return of education due to higher school quality would induce parents to send their children to school. Beegle et al. (2008) use panel data as opposed to Boozer and Suri (2001) who use cross-sectional data from Ghana. Other studies that have used the IV approach include; Rosati and Rossi, 2003; Ray and Lancaster, 2003; Gunnarsson, Orazem, and Sanchez, 2006.

With the availability of panel data, one can expand the type of analyses to allow for fixed effects. This would allow for better control over the endogeneity between schooling and hours of work by accounting for household level, child level, and/or cluster level fixed effects. This paper will discuss the problem of estimating the impacts of child labor on schooling by comparing different specifications and explaining the advantages and disadvantages of each type of model.

III. Data and Background

This study uses household level data from the first four interview waves of the Kagera Health and Development Survey (KHDS). Kagera is located in the northwestern region of Tanzania and is bordered by Lake Victoria on the east, Burundi and Rwanda on the West and Uganda in the North. The KHDS was conducted across six districts in the Kagera region of Tanzania. It includes interviews of 840 households, which resulted in 6353 original respondents. The survey includes urban and rural households. Information was collected on household and individual level demographics, including income, work, health, education, and mortality. In addition, the data includes community level information on health facilities, primary schools, markets, and traditional healers. The KHDS also contains information on the price levels experienced at the different villages.

The household interviews were conducted from 1991-1994 according to the following schedule:

Wave 1 – September 1991-May 1992

Wave 2 – April 1992-November 1992

Wave 3 – November 1992-May 1993

Wave 4 – June 1993-January 1994

Of the original 840 households, 90.4% were re-interviewed at Wave 4.

The relevant sample of interest is children who are 7 to 14 years old at any of the four waves. As Ainsworth, Beegle, and Koda (2005) explain, there is higher likelihood that children will either drop out of school altogether in high numbers by age 15 or when they do attend secondary school, they will do so at very low rates. Therefore, limiting the sample of children to these ages will avoid this possibility, while focusing on children who are likely to have started primary school and being subject to higher likelihood of interrupted enrollment. The baseline sample is 5258 children.

Rainfall data is available from a supplement to the KHDS. Monthly rainfall data is available for 21 weather stations from 1980 to 2004. The climate of Kagera is such that there are typically two rainy seasons along with two dry seasons. The long rainy season occurs from March to May and the short rainy season occurs from October to December and the remaining months constitute the two dry seasons. The rainfall data supplement to the KHDS contains monthly rainfall in millimeters according to the closest and second-closest weather stations to a specific cluster. Data is recorded according to the distance to the nearest weather station. Distance is measured in two ways: 1) with direct-line estimates from the village centers to the nearest and second nearest rainfall stations, and

2) with distance measures that take into account the topology from the village center and the nearest and second nearest rainfall station locations. There are some stations in each group that have missing data.

a. Variables of Interest

I will look at the impacts of child work on schooling. Specifically, the dependent variables will include: 1) an indicator variable whether the child dropped out of school at any point during the four waves even if there is re-entry, 2) an indicator variable for whether the child was enrolled in school at the time of interview, and 3) the grade attained minus expected grade for age for those children who are enrolled throughout the waves observed. Whether the samples are pooled or not pooled will depend on the method used and will be described more fully in the empirical methods section.

Enrollment in school may change wave-to-wave due to short-term circumstances in the child's life. In all dropout analyses, the child is enrolled at the first point of observation, which does not necessarily mean the first wave, so that the child is subject to the risk of dropping out of school. Although children can re-enroll, the dropout indicator will equal 1 if the child was not enrolled at any of the waves following the first point of observation. Therefore, the dropout variable is able to more fully capture the cumulative effects of work hours that induce a child to not attend school. Dropout is constructed through the use of the enrollment variable and, therefore, these two variables will have significant correlations.

Unlike the dropout analyses, the enrollment specifications are not subject to any sample restriction. Enrollment status can be endogenous to the cumulative effects of a specific child's previous history. In other words, when the child is observed as enrolled or not enrolled at the first point of observation, it may be due to circumstances that occurred prior to the point of observation.

The construction of the grade minus expected grade for age variable follows from Orazem and Gunnarsson (2004) who suggest that such a variable measures schooling success that is independent of age. Specifically, with the independent control variable for the age of the child, this variable distinguishes between the effects of keeping the child in or out of school because he/she is ahead/behind and the decision of schooling based on the age of the child. The grade minus expected grade for age variable is constructed by taking the difference between the grade attained at the interview and the grade the child is expected to have attained by given his/her age. In terms of the expected grade for age, I use two types: 1) the worldwide norm of the grade for age, and 2) the mode of the grade attained for the KHDS sample. In the main results, the worldwide norm of expected grade for age variable is used. For example, a 7 year old child is expected to be in the 2nd grade, an 8 year old is expected to be in 3rd grade, and so on. Estimations using the KHDS sample's modal grade minus grade for age variable are included in the sensitivity analyses. In both the modal and norm versions of the variable, grade attained is simply the highest level of formal schooling the child has completed at each wave. For the enrolled sample of the children 7 to 15 years old, the highest grade attained is less than the 7th grade for most of the sample. This supports the use of the modal version of grade minus grade for age variable in the sensitivity analyses.

In this paper, child labor is measured by summing chore hours inside the home and economic hours on agricultural production. Assaad, Levison, and Zibani (2003) explains that an important determinant of whether Egyptian girls attend school is domestic work. In addition, Levison and Moe (1998) and Levison, Moe, and Knaul (2001) show that whether there exists measured substitution between work and educational attainment depends on whether domestic work is included in total hours worked. Domestic hours and its higher propensity of negative impact on younger girls justify the use of chore hours as an important determinant of schooling outcomes. Similarly, gender roles seem to suggest that agricultural work is more prevalent among males in a household. In the KHDS, these variables are measured by asking the main respondent the hours worked by the child over the past seven days. Chore hours include time spent collecting firewood, getting water, preparing meals, cooking, and cleaning. Agricultural hours include tending of crops, processing crops, and tending livestock. The sum of chore hours and agricultural hours constitute the total hours worked. In order to observe possible lagged effects on the outcome variables, hours of work from the previous interview are used in the main specifications.[1] Current hours of work by the child, which is the observed hours of work at time of interview, is used in the alternate specifications.

The grade minus grade for age results give an intensive margin assessment of the impacts of hours of work on schooling status, because it looks at how far a child falls behind given that he/she works more hours. The dropout and enrollment variables results describe the extensive margins of child labor in that we are looking at whether children are induced to stop or leave schooling altogether.

b. Rainfall Instrument

[1] For estimations which use lagged hours of work, all estimates will exclude Wave 1 of the KHDS since there are no lagged hours available.

In order to retain as much data as possible, the rainfall variables were constructed in three steps. First, missing rainfall information from the nearest rainfall station according to topologically accounting distance was replaced by non-missing data from rainfall station data with the shortest direct-line distance to the cluster. Second, the missing rainfall data from the second nearest rainfall station according to topological distance was replaced by non-missing data from the second nearest direct-line rainfall station. Third, missing rainfall data from the nearest stations was replaced with non-missing data from the merged data of the second nearest stations. These steps result in precipitation data that has no missing observations.

Since the KHDS occurred from 1991-1994, I use rainfall data only from 1980-1994.[2] According to the Kagera regions climate, the rainfall information was categorized into four seasons: 1) Dry Season 1 (January-February), 2) Long Rainy season (March-May), 3) Dry Season 2 (June-September), and 4) Short Rainy Season (October-December). The long-run precipitation average was calculated by taking the mean seasonal data from 1980-1994. Thereafter, by taking the difference between the realized seasonal rain in 1991-1994 and the long-run averages, I calculate the deviations from the mean precipitation levels. The data are standardized so that the variable is expressed in units of standard deviations from the mean.

The rainfall instrument will be the set of variables of seasonal rainfall deviation from the 14-year average. In all estimations that use the instrumental variable approach, the rainfall instrument will correspond to the time in which the work hours are observed.

[2] Using data from 1980 allows me to create a trustworthy long run rainfall average.

Hence, the lagged hours of work specifications will correspond with lagged rainfall and current rainfall will correspond with current hours of work.

I expect rainfall to be a significant input to agricultural output. Hence, it could influence the use of child labor within the household. High rainfall deviation from the average could increase the marginal productivity of child labor and induce households to increase the child labor input to increase the use of child labor.[3] Rainfall is also expected to be independent of schooling status. More of the issue of the exclusion of rainfall from schooling status is discussed in section VI(a).

c. Other Covariates

Household composition measures are included as controls in order to account for the possibility that different types of households may have propensity to send or not send the child to school. Household composition is measured by the following variables: number of children under 7 years old, number of children 7-15 years old outside of the focal child, number of adolescents 16 & 17 years old, number of adults 18-55 years of age, and number of seniors above 55 years of age. These are all calculated according to gender to differentiate the gender specific effects. In order to account for additional housework that may occur due to household illness, the number of acutely ill adults 18-55 years of age and the number of chronically ill adults 18-55 years of age is also taken into account.

The parents' baseline level of education is included to account for the possibility that socioeconomic status might affect whether children go to school or work. For children who experience a parental death prior to the first wave, the highest grade

[3] While this logic seems valid, lack of consistent power in the rainfall instrument is seen in the joint statistical significance of the first-stage regressions (Table 14). This is taken into account when discussing the results of the IV estimates and will be elaborated on later in the paper.

completed of the dead parent according to the primary respondent is used as the baseline level of education. For those with a non-deceased parent, I use the respective parent's highest grade completed at the first observation point. Given the definition of a household in the KHDS can include multiple families, it is possible to have multiple parents for children within a household. However, using the methods described above, I was able to reconstruct the majority of the parents education levels. The parents' levels of education will appear in the household level fixed effects as well as the cross-sectional models.

We can expect wealthier households to rely less heavily on child labor. Therefore, a measure of assets is used to account for the possibility of heterogeneity in child labor use due to wealth differences is included. Total household asset value by wave is available in the KHDS. In the cross-sectional and pooled analyses that follow, as a proxy for wealth and credit constraints, I use the log of total asset value per capita at each wave. These values are inflation adjusted prior to taking the logs.[4]

In the interest of controlling for gender roles, I include wave-to-wave household deaths according to gender. These deaths were categorized according to age and include less than 7 years old, 7 to 15 years old, 16 and 17 year olds, 18 to 55 year olds, and seniors above 55 years of age. In the case of prime-aged adults from 18 to 55 years old, the deaths are categorized according to gender.

d. Descriptive Statistics

In order to get a general overview of the samples, the descriptive statistics are of pooled observations across all of the four waves of the KHDS. Therefore, some children

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[4] Due to some households reporting no asset value, all observations were normalized to have 1 as the lowest value of assets prior to taking the log. This ensures that an ordinal value comparison of households' wealth is still possible.

are observed repeatedly.[5] Three subsamples are created for the different analyses based on the following restrictions: 1) The subsample for the dropout analyses is restricted to include only those children who are enrolled at the first interview, 2) the enrollment subsample includes all children (and therefore the highest number of observation points), and 3) the subsample for the grade minus norm grade for age variable includes children who were enrolled throughout all the waves.[6] These sampling restrictions are imposed throughout all descriptive statistics and estimations.

Tables 1 to 3 outline the summary statistics of the baseline subsamples for dropout, enrollment, and grade minus expected grade for age. On average about 4 percent of those enrolled at the first interview experience dropout. Throughout all interview waves, 66 percent of all children are enrolled. Of those who are enrolled throughout all the waves, children were on average behind by approximately 4.6 years of schooling. Throughout all three subsamples, children on average work 18 hours per week. Fathers of children had on average two years of education more than the mothers. The household composition remains the same throughout the three subsamples.

In the child fixed effects framework, considering children who are only observed once are dropped, a more visual representation of the main variables is useful. Panel A traces out the percent of children not enrolled, dropped out, and falling behind. Figures A1 and A2 traces out the behavior of enrollment and dropout variables conditional on being observed twice, three times, and four times. An observation point does not always coincide with the same waves of the KHDS. While the percent not enrolled falls with time, implying more children are entering school as time goes on, the dropout rate is

[5] Note that in panel data estimation methods, children are stratified according to wave.
[6] The grade minus grade for age variable in the main results uses the worldwide norm expected grade for age.

increasing with time. Those observed three or four times have a higher dropout rate than those only observed twice. These trends suggests, that the risk of dropout out increases with time. Figure A3 traces the mean grade minus grade for age for the different ages. This figure shows that, on average, children are falling behind further as they grow older.

In terms of hours of work, the wave-to-wave comparison given in figure B1 does not say much about how hours change with time. However, figure B2, which traces hours of work according to age groups 7-9, 9-11, 11-13, and 13-15, suggests that hours worked increase with age with all categories of work. Further breaking this by gender in Panel C, a more detailed account of the hours of work is outlined. Comparing figures C1 and C2, female children, on average, experience a higher burden of hours worked relative to males. Chore hours are significantly higher for females than males. In addition, male children's economic hours increase significantly from age 11-13 to 13-15 years. However, their chore hours stabilize at 11. A seemingly slowing trend in economic hours is shown in figure C1 for females. The trends align with previous work on gender roles, which suggest economic hours may be more important for male children, while chore hours are important in determining female children's work hours.

Table 4 to 6 show the dependent variables against the hours worked according to age groups. For the most part non-enrollment, dropout, and negative grade minus grade for age (falling behind), are associated with higher hours of work. This negative relationship between grade minus norm grade for age is not clear. This may be due to the construction of the variable itself and later sensitivity tests using the grade minus modal grade for age variable show a more significant negative relationship in the descriptive statistics.

IV. Empirical Strategy

This section discusses the different models that I use to identify the impacts of child labor on schooling. The baseline ordinary least squares and probit models, along with the two-stage least squares and household fixed effect approach will use cross sectional data. Taking advantage of the panel structure of the KHDS, I also estimate child level fixed effects models and the child level fixed effects with the rainfall instrument. While there is bias in the estimates due to unobserved heterogeneity, this bias is expected to decrease with each consecutive model, the child level fixed effects with IV is the least efficient model.

a. Baseline Probit and Ordinary Least Square Models

The observed values of the indicated child enrollment or dropout are determined by an underlying unobserved variable Y_i^* . Given this latent variable, however, the outcomes equal either 1 or 0 according to the following equation:

$$Y_i = 1(Y^*_i \geq 0) = 1(\beta_1 X_i + \beta_2 Hours_i + e_i \geq 0)$$ [7]

This equation implies that the likelihood of the outcome can be estimated using binary models. I use the probit model for estimating the binary outcomes of dropout and enrollment. The marginal effects estimates are calculated holding the indicator independent variables to zero and continuous variables at their means. These marginal effects are the estimates presented in the results section for all the enrollment and dropout estimations.

Given the continuous structure of the grade minus grade for age variable, I use an OLS regression as a baseline model for this variable:

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[7] The '1' indicator is simply the binary indicator. Y_i=1 if the condition in the parenthesis for the latent variable holds.

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Hours_i + e_i,$$

X_i in this cross-section framework will include covariates that will be absent within the child fixed effects framework (examples: parents' baseline level of education and gender of the child). Given these basic OLS and Probit specifications, the variation in $Hours_i$ will include separate specifications for current hours and lagged hours.

The above specifications do not account for the endogeneity between hours of work and schooling statuses. β_2, in both the OLS and probit estimates, will only allow inference about the correlation between *Hours* and Y_i and says little about the direction of causality. Even specifications that use the lagged hours of work will still suffer from unobserved heterogeneity in the error term. Therefore, the coefficients will be biased due to both time varying and time invariant unobservables.

b. Instrumental Variable Approach

In the case of the binary outcomes of dropout and enrollment, I use the instrumental variable probit model. Here, the first stage calculates the linear model of the hours of work on the independent variables and the rainfall instrument. Thereafter, maximum likelihood is used to estimate the second stage probit model, while taking into account that the hours of work variable is endogenous. This method generates more precise estimate of the standard errors. The marginal effect estimates, with binary variables held at zero and continuous variables held at the means, are presented in the results section.

For the case of the grade minus norm grade for age variable, the 2SLS approach is utilized. In the first stage of the IV specification, the following is estimated:

$$Hours_{ihct} = \beta_0 + \beta_1 X_{ihct} + \beta_2 RainfallDeviation_{ct} + e_{ihct},$$

where i is child, h is household, c is cluster, t is round of survey, and X_{ihct} is the set of all other covariates. Note that rainfall data is observed at the cluster level.

In the second stage, the model is specified as follows:

$$Y_{ihct} = \beta_0 + \beta_1 X_{ihct} + \beta_2 \widehat{Hours}_{ihct} + e_{ihct},$$

Both the probit IV and the 2SLS models identify the impact of changes in hours on schooling across different children. However, since the rainfall instrument is measured at the cluster level and the deviations might not vary as much across children within the same cluster, there is a concern about the relative power of the instrument in explaining variations in hours across children. Similarly, the exclusion of rainfall may be in question as communities with higher rainfall may already be more affluent. This phenomenon implies that the marginal returns of schooling for a child in a village that receives larger amount of precipitation may be higher. Schooling decisions are, therefore, affected by rainfall in this scenario.

c. Household Level Fixed Effects

The household level fixed effects will be slightly different in that all common time-invariant household level variables are removed. The outcomes can be decomposed into child-specific and household-specific components. For each child within the household:

$$Y_{ihc} = \beta_{0ihc} + \beta_1 X_{ihc} + \beta_2 Hours_{ihc} + \rho_{hc} + u_{ihc}$$

The regressions are stratified by wave and estimation occurs through the deviations of the child level variables from the averages observed within children of the same household:

$$Y_{i/hc} - \bar{Y}_{hc} = \beta_1 (X_{i/hc} - \bar{X}_{ihc}) + \beta_2 (Hours_{i/hc} - \overline{Hours}_{ihc}) + (\rho_{hc} - \bar{\rho}_{hc}) + (u_{i/hct} - \bar{u}_{ihc})$$

ρ_{hc} is the household level fixed effects which is differenced out since this is the same for all children. The household level averages are $\bar{Y}_{ihc}$, $\bar{X}_{ihc}$, $\overline{Hours}_{ihc}$, and $\bar{u}_{ihc}$. Note the assumption that $(u_{i/hct} - \bar{u}_{ihc})$ being uncorrelated with all the observed values of $(X_{i/hc} - \bar{X}_{ihc})$ and $(Hours_{i/hc} - \overline{Hours}_{ihc})$ are needed to consistently estimate the parameters of this equation.

The identification of the household level fixed effects is based only on the differences in work hours for children within the same household. These children are not necessarily siblings, since there can be multiple families within a household unit in the KHDS. This model has a disadvantage in that there is still the possibility of reverse causality. Parents may have decided to pull the child out of school prior to the additional hours of work observations. Another source of endogeneity is that households may pick which child works and does not work based on child specific unobservables. In other words, households and parents may decide to send children who they believe are more likely to succeed in academics to school, while others who are perceived to have higher economic returns outside of school stay at home and work. A third concern is that, since the household fixed effects is conducted by wave, there is no way to control for time varying factors that affect schooling and work hours simultaneously. Nonetheless, this model is a useful benchmark for comparison similar to the pooled and IV models.

d. Child Level Fixed Effects

In the child level fixed effects, the outcomes of the child take the following form:

$$Y_{ihct} = \beta_1 X_{ihct} + \beta_2 Hours_{ihct} + \delta_{ihc} + u_{ihct},$$

δ_{ihc} designates the child level fixed effects and u_{ihct} is the child level time varying unobservable. This child fixed effect, δ_{ihc}, is differenced out when conducting the child level fixed effects estimation:

$$Y_{ihct} - \bar{Y}_{ihc} = \beta_1(X_{ihct} - \bar{X}_{ihc}) + \beta_2(Hours_{ihct} - \overline{Hours}_{ihc}) + (u_{ihct} - \bar{u}_{ihc})$$

Where the child level averages are $\bar{Y}_{ihc}$, X_{ihct} , $\overline{Hours}_{ihc}$, and $\bar{u}_{ihc}$. For the child level fixed effects to be consistent, the $(u_{ihct} - \bar{u}_{ihc})$ is assumed to be uncorrelated with $(Hours_{ihct} - \overline{Hours}_{ihc})$ and $(X_{ihct} - \bar{X}_{ihc})$. In other words, the time varying unobservables are uncorrelated with the variables specified in the regression.

The advantage of this model is that the time invariant characteristics of the child, the household, and the community are differenced out. All that is left in the error term is time varying factors that affect schooling and education status. Note that these two types of factors may be correlated. While the child fixed effects estimation may therefore deal with much of the endogeneity between hours and schooling, it is not able to completely eliminate the simultaneity in hours of work and schooling decisions.

e. Child Level Probit Random Effects with IV

As a comparison to the child level fixed effects coefficients on the binary outcomes of enrollment and dropout, I estimate a two-stage random effects probit model through the use of instruments. [8] A concern with this model is that it assumes no correlation between the error term and the explanatory variables. The possibility of correlation between the error term and the explanatory variables is, however, less likely given the omission of non-random variables, such as ability.

f. Child Level Fixed Effects with IV

[8] A fixed effects probit model with instruments is not possible.

In the first stage, rainfall is used to instrument for child labor hours. In the second stage, the predicted child labor hours will be used to analyze the impact of labor hours on all schooling outcomes (dropout, enrollment, and grade minus grade for age). Below is a simple outline of the estimation procedure.

In the first stage, the following is estimated:

$$\begin{aligned}(Hours_{ihct} - \overline{Hours}_{ihc}) \\ &= \beta_1(X_{ihct} - \bar{X}_{ihc}) + \beta_2(RainfallDeviation_{ct} - \overline{RainfallDeviation}_{c}) \\ &+ (e_{ihct} - \bar{e}_{ihc})\end{aligned}$$

$\ddot{\widehat{Hours}}_{ihct}$ is the deviation of hours from the mean hours observed for each child. I use this to calculate the second stage:

$$Y_{ihct} - \bar{Y}_{ihc} = \beta_1(X_{ihct} - \bar{X}_{ihc}) + \beta_2 \ddot{\widehat{Hours}}_{ihct} + (u_{ihct} - \bar{u}_{ihc})$$

This model has the same advantages of the child level fixed effects model, but also has better estimates in light of the simultaneity of the hours of work and schooling decisions. The estimates are more reliable when a strong instrument is used. I believe this is the most preferred model for measuring how hours of work affect schooling decisions when panel data are available.

V. Results

The first column of Table 7 displays the results for the most preferred model; the child level fixed effects model with the rainfall instrument and with lagged hours as the endogenous independent variable. Overall the estimates suggest that for 10 hours of work, dropout rates increase by 6.3 percent. While this is about a one-tenth increase in dropout, it is not statistically significant. The random effects probit with IV estimate, however, is statistically significant and shows an estimate closer to the IV probit specification in column 4 and is more than 10 times the point estimate in column 1. This suggests that there is significant bias and inefficiency in random effects probit estimate. There is a marginally significant, 16.1 percent decrease in enrollment due to 10 hours of work. This is approximately a one-seventh increase in the number of children who have disrupted enrollment. The random effect probit with IV estimate is statistically significant and shows that for 10 hours of work, enrollment falls by approximately 93 percent. This again is closer in magnitude to the probit with IV result outlined in column 4. In terms of being behind in grade, a ten-hour increase in lagged hours of work per week leads to over half a year drop in grade attainment for a given age. Given that most of the children are already behind, this result suggests that hours of work is a significant deterrent to school attendance. The child level fixed effects results displayed in the third column of Table 7 tell a similar story, except in the case of the positive, but insignificant, impact of lagged hours on enrollment. These results are, however, subject to bias due to endogeneity with time varying child level unobservables. Going from the pooled models to the panel models brings more inefficiency, while bias in the estimate decreases. While the lagged hours specification in the panel data estimates above mitigates the concern of simultaneity, however, reverse causality still remains a concern.

Table 8 presents the impact of current hours of work on the different variables of interest. The purpose of the estimates with current hours is to demonstrate the contrast to the results of the lagged hours and clarify how reverse causality is a factor to be taken seriously in this area of work. Contrary to the estimates in Table 7, the child level fixed effects with instrument results show that hours of work have a negative impact in dropout, with 10 hours of work decreasing dropout by 16.1 percent. This effect jumps to a statistically significant 93 percent in the random effects probit with instrumental variables. Similarly, 10 current hours of work increase enrollment by 8.8 percent, although this impact is not significant. The random effects estimate of 10 hours of work on enrollment is approximately negative 89 percent. This estimate is closer to the IV probit results. The child fixed effects with IV estimates are primarily due to the reverse causality of schooling status on hours of work. Children may be working more, because they are not enrolled or have already dropped out. The impact of hours of work on the intensive margin measure of grade minus grade for age is also biased upward due to the same issue of reverse causality. Ten hours of work decreases grade attainment by 35 percent for a given age instead of the more larger 57 percent measure found in the lagged hours specification. The child level fixed effects estimates, while mostly insignificant, show some contradictions to the lagged hours results; there is a negative impact of hours on enrollment status and an increase in 10 hours of work increases the grade attained by 2.8 percent. These results, together with the estimates in Table 7, suggest that one needs to be careful in addressing reverse causality even in the most efficient panel data models. The full estimations with all of the independent variables are included the Appendix.

VI. Sensitivity Analyses

a) Exclusion of Rainfall as an Instrument

As can be seen from the IV specifications, rainfall is used as an instrument although it is calculated at the cluster level. One argument that could potentially compromise the use of rainfall as an instrument is that children who live further from a school may be more adversely affected when there is high rainfall. This argument would question the exclusion of rainfall as an instrument since it would imply that rainfall has an impact on school attendance as well as hours worked. Given that the main focus of this paper is the child level fixed effects models, the estimates in this model are consistent, if the assumption of the exclusion of the rainfall deviations from the mean is not correlated with the changes in schooling status.

In order to check the exclusion of rainfall in light of distance to the nearest school, I use the following assumptions. First, I assume that younger children are more susceptible to have disruption in schooling status if deviations from cluster level mean rainfall make commuting to school difficult. Younger children are also less likely to work given parents' optimizing future potential outcomes by sending their children to school early, while they are still not physically strong enough to handle household or farm work. If higher precipitation from the average does not cause commuting difficulties for younger children, older children, who are relatively stronger physically, are less likely to interrupt schooling due to deviations in rainfall.

In conducting the test, I first limit the sample to children who are 7-9 years old. The tabulation of hours worked by these children suggests that this group works fewer hours than the older cohorts of 10-15 year olds. Older children work on average 20.62 hours with a standard deviation of 14.66 hours. Younger children, on the other hand, work 10.35 average hours with a standard deviation of 11.34 hours. Panel D of the Appendix, which traces hours of work according to the different age groups, shows that of the children 7 to 9 years old, about 60 percent work less than 10 hours in the past 7 days. This safely suggests that 7-9 year olds have a relatively low number of hours worked.

Given the 7 to 9 year old child sample, I use standardized deviations from the mean cluster level distance to the school as an independent variable.[9] I generate these values according to wave. I create an interaction term of the change in deviations from schooling distance with changes in rainfall deviations. Recall that the changes in rainfall deviations are at the cluster levels. In sum, I conduct the following fixed effects regression:

$$Y_{ihct} - \overline{Y}_{hc} = \beta_1(X_{ihct} - \overline{X}_{ihc}) + \beta_2(RainfallDeviation_{ct} - \overline{RainfallDeviation}_c) + \beta_3[(RainfallDeviation_{ct} - \overline{RainfallDeviation}_c) * (schooldistance_{ihct} - \overline{schooldistance}_c)] + \beta_4(schooldistance_{ihct} - \overline{schooldistance}_c) \quad + (e_{ihct} - \overline{e}_{ihc})$$

The results of these regressions are outlined in Table 9. The joint significance test of the *rainfalldeviation*schooldistance* variables suggest that rainfall is excludable in the enrollment and grade minus grade for age specifications, while this is not the case in the dropout regressions. This finding suggests that more weight should be given to the enrollment and grade minus grade for age results. In the case of dropout, one problem with the regression is the fact that school distance is only measured for children who report attending school in the 12 months prior to the interview.

b) Grade Minus Modal Grade for Age

In the estimations below, I use the modal expected grade for age to construct the grade minus grade for age variable. In other words, for each age, the grade for which there is the highest number of children observed in the KHDS data set is the expected grade. Given that children in Kagera may start school late due to circumstances other

[9] Few individuals in the sample, approximately 2% of the sample, do not live at home while attending school. In addition, for children who do attend school and live at home, there is little heterogeneity in school distance as there is usually one school per cluster.

than child labor (example: community norms) this modal variable is a useful way of checking the sensitivity of the previous results. Table 11 presents the average hours of work according to age for the grade minus the modal grade for age variable. There are no children from 7 to 9 years old who are behind. In this part of Tanzania children do not start going to school in high numbers until age 11. In addition, there are two interesting facets about these averages: 1) child labor hours increase with age and, 2) older children (13 to 15 years old) who are behind work more hours than children who are on pace or ahead. The latter observation is contrary to the previous bivariate summary statistics of average work hours and the grade minus norm grade for age variables.

Table 12 and 13 are the results using lagged hours and the current hours, respectively. The most preferred estimation of the child fixed effects with IV shows that a 10 hour work hour increase causes the child to fall behind during the year by 57 percent. This point estimate is the same as the grade minus norm grade for age specification. The magnitude of the effect falls to negative 23 percent with the use of current hours. The fixed effects results seem to contradict each other between the lagged hours and current hours specifications. A 10 hour increase in lagged hours leads to a significant but small drop in grade minus grade for age (-1.8%), while the specification in the fixed effects framework leads to a positive, significant, 3% rise in grade minus grade for age. This reflects the issue of reverse causality, which was present in the normative grade minus grade for age estimation. Overall, the results using grade minus grade for age are consistent across the different definitions of expected grade.

VII. Conclusion

This paper outlines the difficulties associated with assessing the impacts of child labor on schooling status. One needs to do careful assessment on the issues of simultaneity and reverse causality when looking at how child labor affects schooling. Simultaneity and reverse causality are still a concern even in panel data models such as the child level fixed effects. Given these concerns, the child level fixed effects with the instrumental variable approach is the highest standard for estimating these effects. This model is able to deal more completely with simultaneity, reverse causality, and endogeneity especially with the use of lagged hours of work as the endogenous variable of interest. Given the different specifications, the child level fixed effects with strong instruments, while more inefficient, is one that estimates with the least bias.

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Table 1: Summary Statistics of Baseline Dropout Sample

Variable	Mean	Std. Dev.	Min	Max
Dropout	0.0405	0.1972	0	1
Total Hours Worked	18.5267	13.4334	0	110
Age	12.1195	2.1668	7	15
Age Squared	151.5750	50.1106	49	225
Female=1, Male=0	0.5005	0.5001	0	1
Log of Real Assets per Capita	4.3241	1.2678	0	11.44
Father's Baseline Education Level	5.6165	3.3437	0	17
Mother's Baseline Education Level	3.9815	2.9445	0	12
# of Acutely Ill Adults	1.2231	1.0823	0	7
# of Chron. Ill Adults	0.3766	0.6284	0	3
Household Composition: Number of…				
Adult Females	1.7267	1.2775	0	9
Adult Males	1.1610	1.0446	0	8
Female Children under 7 years old	0.8647	1.0222	0	5
Male Children under 7 years old	0.8095	0.9338	0	5
Female Adolescents 16-17 years old	0.2767	0.5165	0	3
Male Adolescents 16-17 years old	0.2743	0.4895	0	3
Female Seniors above 55 years old	0.3162	0.5453	0	3
Male Seniors above 55 years old	0.3024	0.4639	0	2
Number of Deaths at Wave				
Female Adult (18-55)	0.0021	0.0453	0	1
Male Adult (18-55)	0.0017	0.0414	0	1
Children (7-15)	0.0021	0.0453	0	1

Adolescents (16-17)	0.0003	0.0185	0	1
Children (<7)	0.0038	0.0613	0	1
Seniors (>55)	0.0082	0.0904	0	1
Interview Month				
February	0.0875	0.2827	0	1
March	0.0937	0.2915	0	1
April	0.0367	0.1881	0	1
May	0.0563	0.2305	0	1
June	0.0745	0.2626	0	1
July	0.0790	0.2697	0	1
August	0.0769	0.2665	0	1
September	0.1020	0.3026	0	1
October	0.1147	0.3187	0	1
November	0.0999	0.2999	0	1
December	0.0985	0.2981	0	1
Number of observations		2913		

Table 2: Summary Statistics of Baseline Enrollment Sample

Variable	Mean	Std. Dev.	Min	Max
Currently Enrolled	0.6608	0.4735	0	1
Total Hours Worked	17.3492	14.5042	0	110
Age	11.1170	2.5724	7	15
Age Squared	130.2041	56.8683	49	225
Female=1, Male=0	0.5026	0.5000	0	1
Log of Real Assets per Capita	4.1451	1.2423	0	11.4385
Father's Baseline Education Level	5.3440	3.2413	0	17
Mother's Baseline Education Level	3.7017	2.9468	0	12
# of Acutely Ill Adults	1.2268	1.0531	0	7
# of Chron. Ill Adults	0.3682	0.6247	0	4
Household Composition: Number of…				
Adult Females	1.6436	1.2129	0	9
Adult Males	1.1375	1.0136	0	8
Female Children under 7 years old	0.8538	1.0159	0	5
Male Children under 7 years old	0.8735	0.9604	0	5
Female Adolescents 16-17 years old	0.2606	0.4967	0	3
Male Adolescents 16-17 years old	0.2468	0.4659	0	3
Female Seniors above 55 years old	0.2914	0.5279	0	3
Male Seniors above 55 years old	0.2809	0.4586	0	2
Number of Deaths at Wave				
Female Adult (18-55)	0.0028	0.0525	0	1
Male Adult (18-55)	0.0022	0.0465	0	1
Children (7-15)	0.0016	0.0397	0	1

Adolescents (16-17)	0.0006	0.0243	0	1
Children (<7)	0.0047	0.0686	0	1
Seniors (>55)	0.0061	0.0779	0	1
Interview Month				
February	0.0816	0.2737	0	1
March	0.0869	0.2817	0	1
April	0.0349	0.1835	0	1
May	0.0518	0.2217	0	1
June	0.0764	0.2657	0	1
July	0.0825	0.2752	0	1
August	0.0877	0.2828	0	1
September	0.0959	0.2945	0	1
October	0.1091	0.3118	0	1
November	0.1042	0.3056	0	1
December	0.1007	0.3009	0	1
Number of observations		5076		

Table 3: Summary Statistics of Baseline Grade – Grade for Age Sample

Variable	Mean	Std. Dev.	Min	Max
Grade – Grade for Age	-4.6237	1.536	-10	4
Total Hours Worked	18.0218	12.9999	0	110
Age	11.7928	2.2453	7	15
Age Squared	144.1094	51.4364	49	225
Female=1, Male=0	0.4952	0.5001	0	1
Log of Real Assets per Capita	4.2983	1.2339	0	11.44
Father's Baseline Education Level	5.6348	3.2915	0	17
Mother's Baseline Education Level	3.9967	2.9073	0	12
# of Acutely Ill Adults	1.2379	1.0848	0	7
# of Chron. Ill Adults	0.3563	0.6157	0	3
Household Composition: Number of…				
Adult Females	1.7275	1.2652	0	9
Adult Males	1.1527	1.0217	0	8
Female Children under 7 years old	0.8691	1.0219	0	5
Male Children under 7 years old	0.8456	0.9569	0	5
Female Adolescents 16-17 years old	0.2752	0.5143	0	3
Male Adolescents 16-17 years old	0.2674	0.4833	0	3
Female Seniors above 55 years old	0.3047	0.5402	0	3
Male Seniors above 55 years old	0.3002	0.4655	0	2
Number of Deaths at Wave				
Female Adult (18-55)	0.0027	0.0517	0	1
Male Adult (18-55)	0.0027	0.0517	0	1
Children (7-15)	0.0021	0.0456	0	1

Adolescents (16-17)	0.0003	0.0173	0	1
Children (<7)	0.0048	0.0689	0	1
Seniors (>55)	0.0069	0.0825	0	1
Interview Month				
February	0.0826	0.2753	0	1
March	0.0886	0.2841	0	1
April	0.0391	0.1938	0	1
May	0.0578	0.2335	0	1
June	0.0838	0.2771	0	1
July	0.0897	0.2859	0	1
August	0.0817	0.2739	0	1
September	0.0984	0.2979	0	1
October	0.1061	0.3081	0	1
November	0.0960	0.2946	0	1
December	0.0951	0.2934	0	1
Number of observations		3354		

Panel A: Tracing Dependent Variables

Figure A1: Percent Not Enrolled Over Time

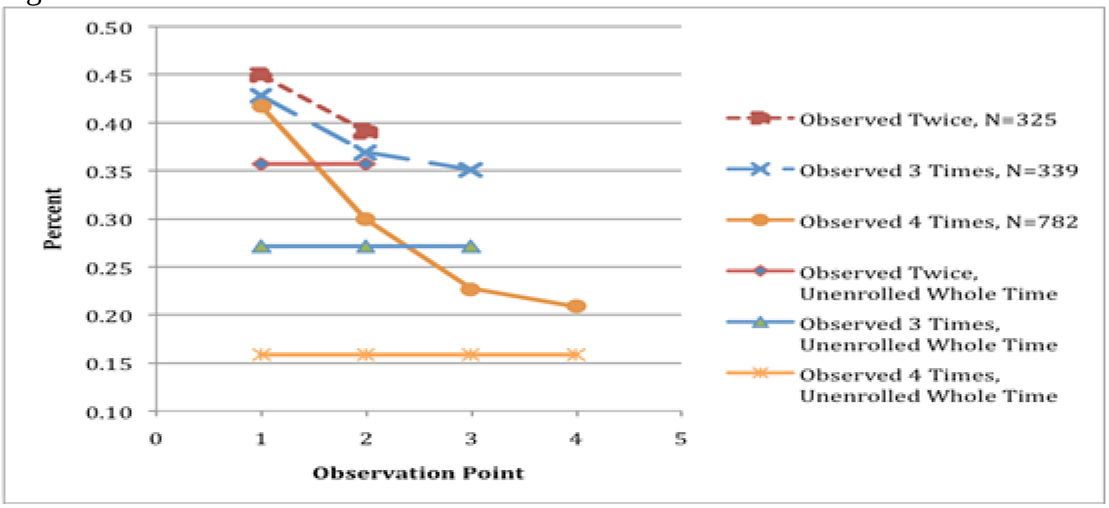


Figure A2: Percent Dropout Conditional Over Time

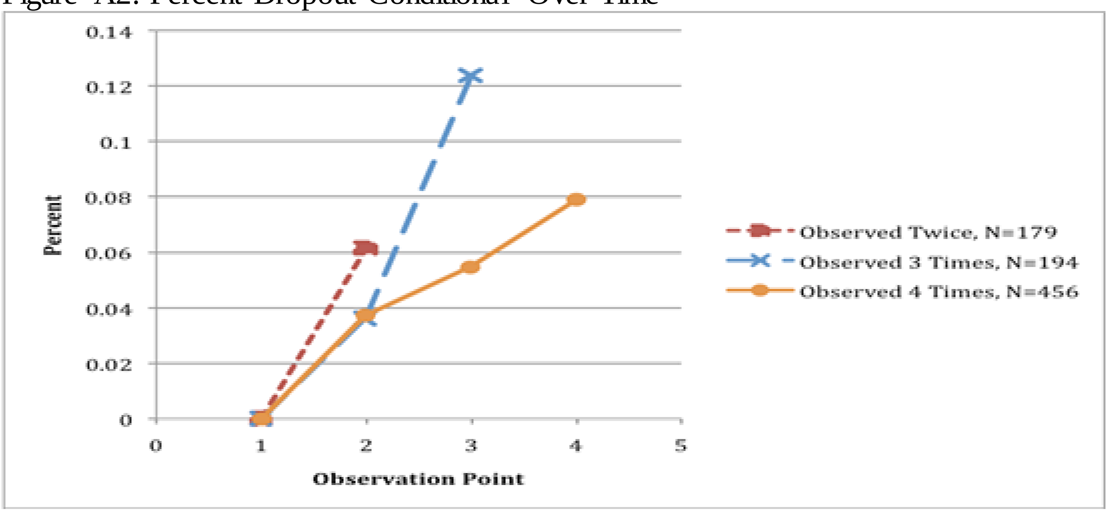
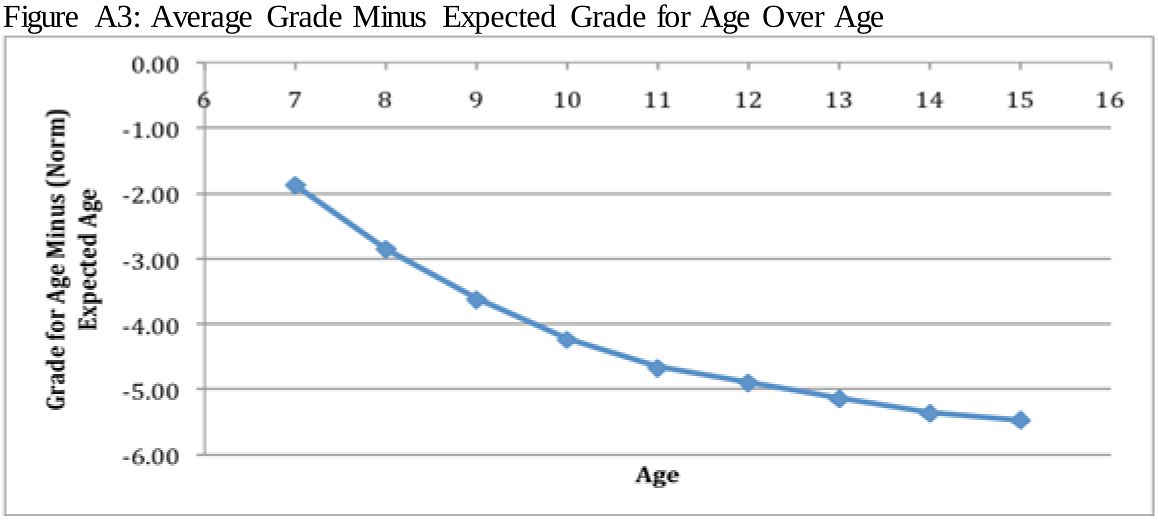


Figure A3: Average Grade Minus Expected Grade for Age Over Age



Panel B: Hours Worked

Figure B1: Hours Worked Wave-to-Wave

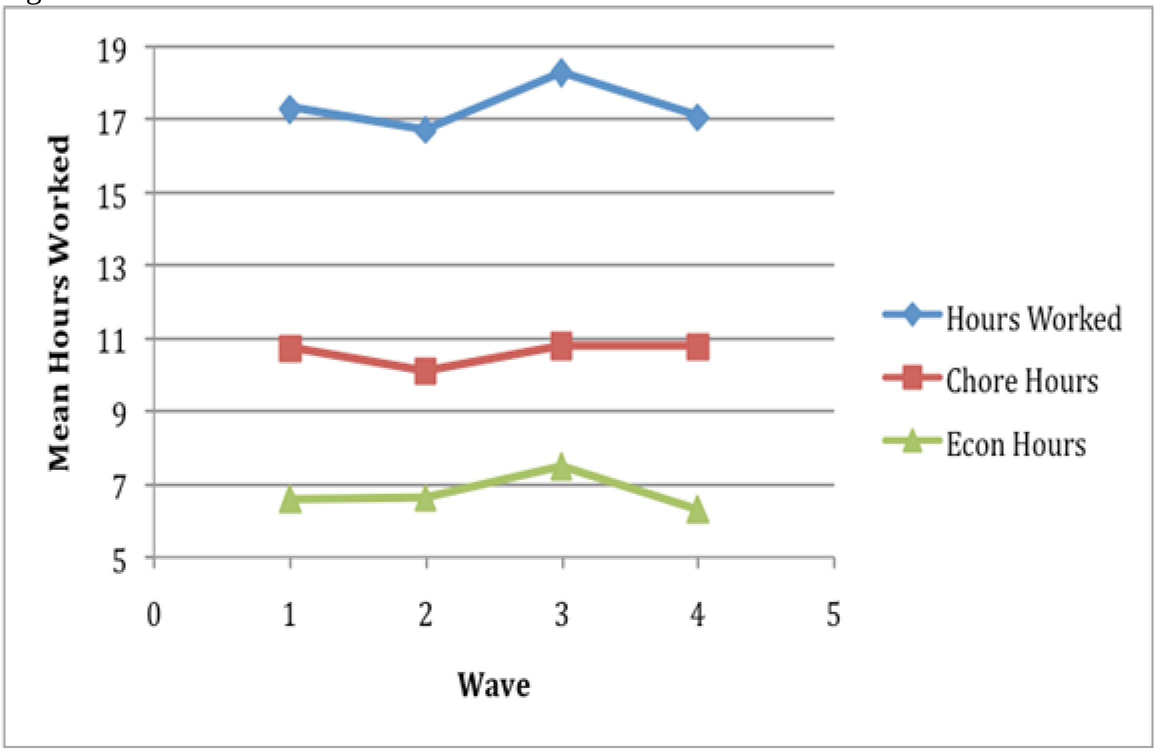
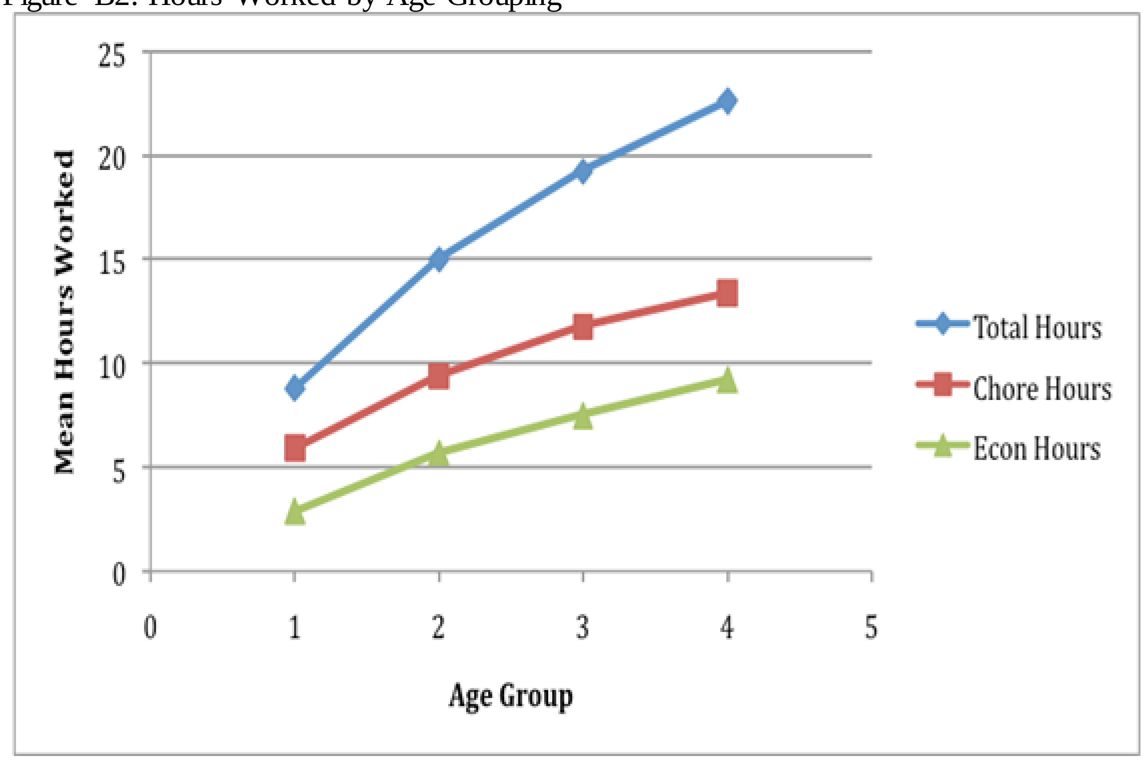


Figure B2: Hours Worked by Age Grouping



[Age group 1 (7-9 years old), age group 2 (9-11 years old), age group 3 (11-13 years old), and age group 4 (13-15 years old)]

Panel C: Hours Worked by Gender

Figure C1: Hours Worked according to Age Group for Females

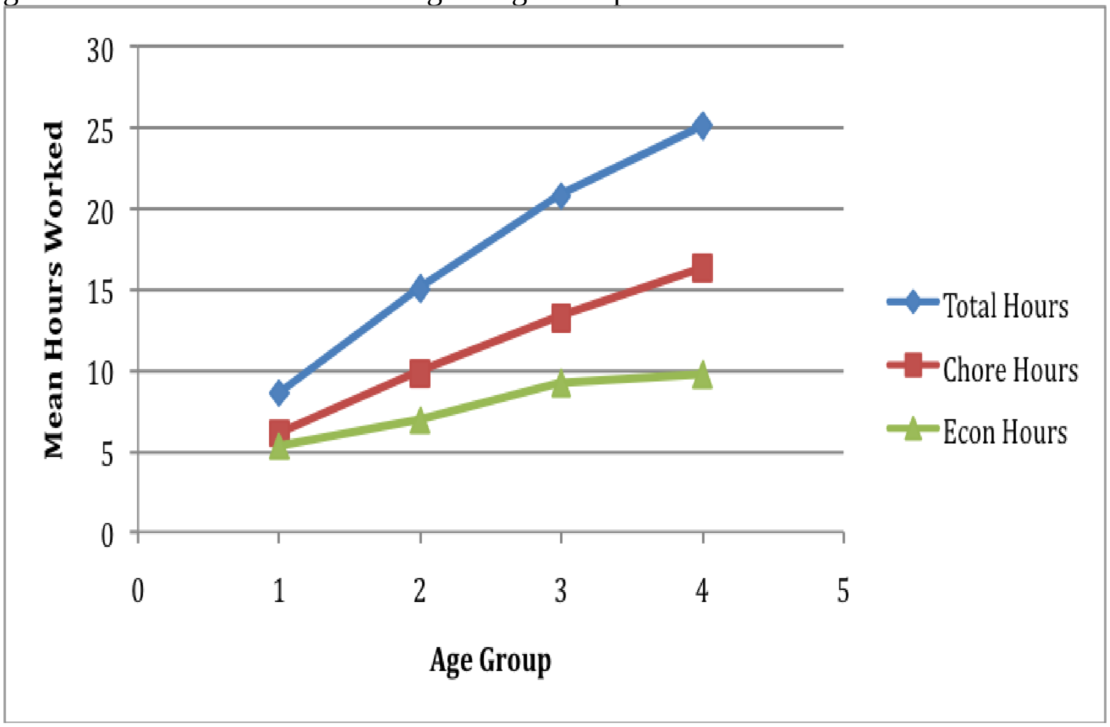
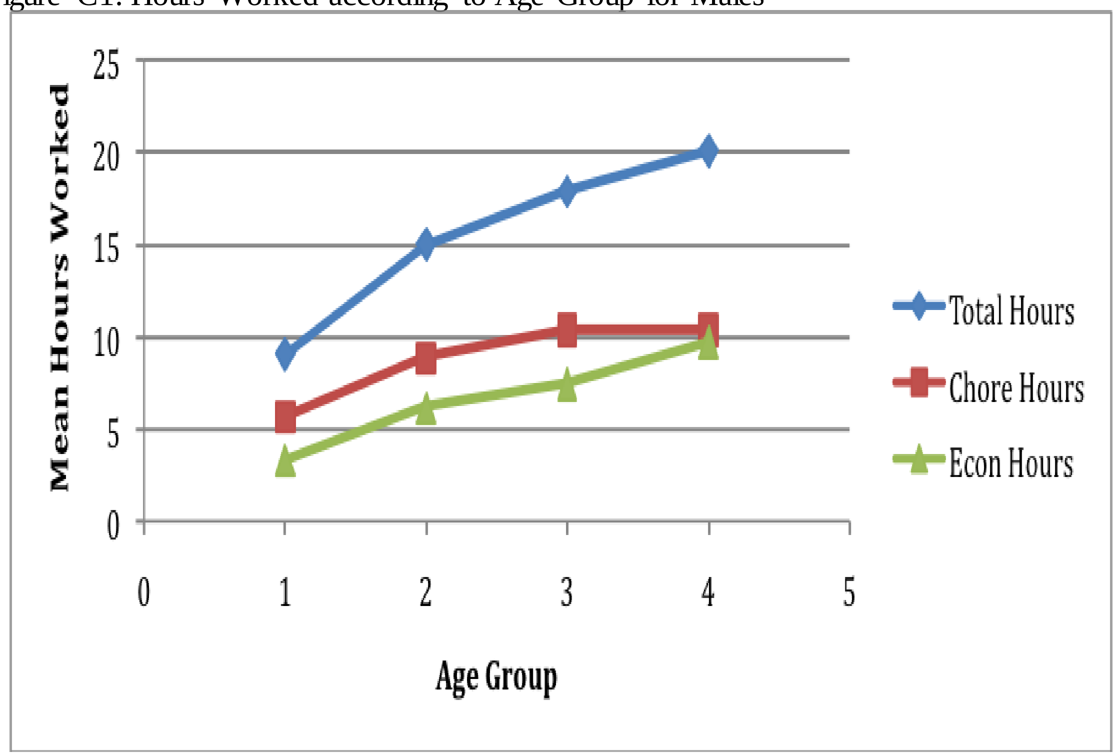


Figure C1: Hours Worked according to Age Group for Males



[Age group 1 (7-9 years old), age group 2 (9-11 years old), age group 3 (11-13 years old), and age group 4 (13-15 years old)]

Table 4: Hours of Work According to Enrollment and Age Group

Variable	Enrollment=0				Enrollment=1			
Age Groups	7 to 9	9 to 11	11 to 13	13 to 15	7 to 9	9 to 11	11 to 13	13 to 15
Total Hours	8.16	15.86	21.82	28.96	10.27	14.50	18.64	21.00
Std. Dev	10.47	15.22	16.90	20.05	10.30	11.14	12.71	13.43
Chore Hours	5.52	9.79	11.12	13.89	6.81	9.06	11.87	13.27
Std. Dev.	7.15	10.48	9.37	11.88	7.58	7.83	8.69	9.01
Econ	2.64	6.07	10.70	15.07	3.45	5.43	6.77	7.73
Std. Dev.	6.21	8.52	11.91	13.42	5.87	6.82	8.03	8.27
N=	750	397	208	370	330	649	942	1433

Table 5: Hours of Work According to Dropout and Age Group

Variable	Dropout=1				Dropout=0			
Age Groups	7 to 9	9 to 11	11 to 13	13 to 15	7 to 9	9 to 11	11 to 13	13 to 15
Total Hours	13.18	16.82	17.31	26.72	8.92	14.37	18.68	20.93
Std. Dev	17.34	11.76	12.83	20.68	9.55	11.13	12.92	13.38
Chore Hours	8.82	8.56	9.11	13.69	5.98	8.84	11.88	13.25
Std. Dev	10.77	7.47	7.11	12.09	6.70	7.71	8.71	8.94
Econ Hours	4.36	8.26	8.20	13.03	2.94	5.52	6.80	7.68
Std. Dev	8.44	8.76	8.55	12.44	5.91	7.07	8.20	8.33
N=	11	16	23	69	213	421	819	1342

Table 6: Grade – Grade for Age According to Age Group

Variable	Grade - Grade for Age >= 0				Grade - Grade for Age < 0			
Age Groups	7 to 9	9 to 11	11 to 13	13 to 15	7 to 9	9 to 11	11 to 13	13 to 15
Total Hours	16.5	15.52	18.05	15.46	16.5	14.49	18.64	21.02
Std. Dev	3.54	13.90	2.76	22.13	3.54	11.13	12.72	13.40
Chores	8.5	11.92	17.05	8.86	6.80	9.04	11.86	13.28
Std. Dev	10.61	12.61	4.17	9.41	7.58	7.79	8.70	9.01
Econ	8	3.6	1	6.6	3.42	5.45	6.78	7.73
Std. Dev	7.07	4.62	1.41	12.86	5.87	6.83	8.03	8.26
N=	2	5	2	5	328	644	940	1428

Table 7: Marginal Effects Estimates of Lagged Hours

	Child Fixed and Random Effects			Pooled Models		Household Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE IV	RE IV	FE	IV/IV Probit	OLS/Probit	Wave 2	Wave 3	Wave 4
Reference Mean	0.0630			0.0637		0.0364	0.0523	0.0475
Dropout	0.0063	0.0961***	0.0001	0.0816***	0.0011*	0.0002	-0.001	0.0007
Std. Err.	0.0043	0.0031	0.0003	0.0015	0.0006	0.0006	0.0095	0.0018
t-stat/z-stat	1.45	30.96	0.19	55.25	1.92	0.25	-1.08	0.40
N	1888			1867		714	727	674
Reference Mean	0.7195			0.7662		0.7117	0.7151	0.7321
Enrollment	-0.0161*	-0.0927***	0.0003	-0.077***	-0.0022***	-0.0002	-0.0007	-0.002
Std. Err.	0.0086	0.0027	0.0004	0.0012	0.0006	0.0012	0.0017	0.0023
t-stat/z-stat	-1.86	-33.89	0.69	-64.34	-3.44	-0.15	-0.46	-0.79
N	3244			3244		1155	1102	989
Reference Mean	-4.7185			-4.7185		-4.7494	-4.5635	-4.8522
Grade Minus Norm Grade for Age	-0.0572***		-0.0016*	-0.1824	-0.0002	-0.0045	0.0055	-0.0005
Std. Err	0.0212		0.0008	0.149	0.0023	0.0051	0.0066	0.0077
t-stat/z-stat	-2.69		-1.92	-1.22	-0.08	-0.88	0.84	-0.07
N	2334			2334		822	788	724

*** p<0.01, ** p<0.05, * p<0.1

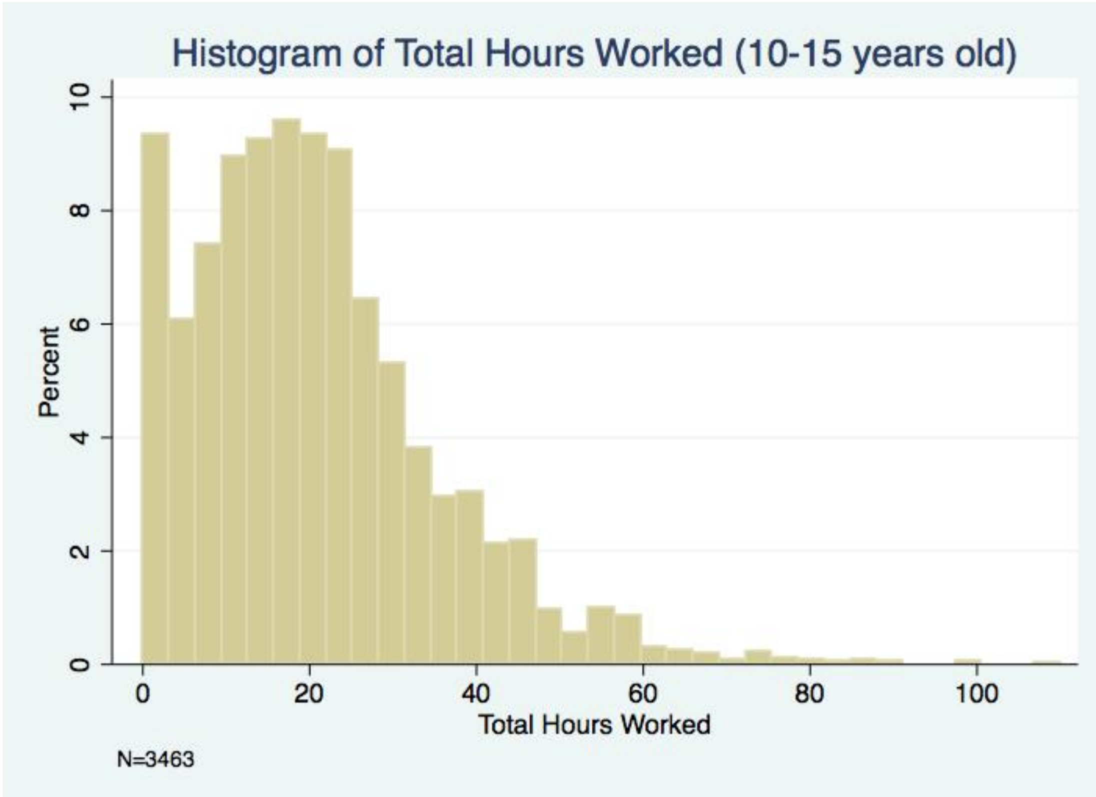
Table 8: Marginal Effects Estimates of Current Hours

	Child Random and Fixed Effect			Pooled Models		Household Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FE IV	RE IV	FE	IV/IV Probit	OLS/ Probit	Wave 1	Wave 2	Wave 3	Wave 4
Reference Mean		0.0405		0.0408			0.0368	0.0506	0.0519
Dropout	-0.0161**	[∀]-0.0924***	0.0005	[∇]-0.0775***	0.0006**		0.0024*	0.0027*	-0.0008
Std. Err.	0.0067	0.0027	0.0004	0.0021	0.0028		0.0014	0.0015	0.0019
t-stat/z-stat	-2.39	-34.18	1.52	-36.44	2.05		1.75	1.75	-0.41
N		2913		2890			707	731	674
Reference Probability/Mean		0.5508		0.6634		0.6022	0.6567	0.6854	0.6922
Enrollment	0.0088	-0.0893***	-0.0004	-0.077***	-0.0031***	-0.0026*	-0.0027*	-0.0035*	-0.0049***
Std. Err.	0.0111	0.0042	0.0004	0.0008	0.0006	0.0014	0.0014	0.002	0.0019
t-stat/z-stat	0.79	-21.33	-1.01	-99.54	-5.18	-1.88	-1.91	-1.73	-2.61
N		5076		5076		1395	1317	1246	1121
Reference Mean		-4.6237		-4.6237		-4.4714	-4.7048	-4.5375	-4.7912
Grade Minus Norm Grade for Age	-0.0345*		0.0028***	-0.0191	-0.0001	-0.0073	-0.0072	0.0006	-0.0044
Std. Err.	0.0206		0.0009	0.0229	0.0019	0.0064	0.0058	0.0069	0.0092
t-stat/z-stat	-1.67		3.17	-0.83	-0.04	-1.14	-1.24	0.09	-0.48
N		3354		3354		840	884	854	776

*** p<0.01, ** p<0.05, * p<0.1

[∀] Months and Months Squared are omitted due to non-convergence in the second stage.
[∇] The set of variables indicating the number of deaths is not included, because the probit model did not converge in the second stage.

Panel D: Histograms of Hours Worked according to Age Groups



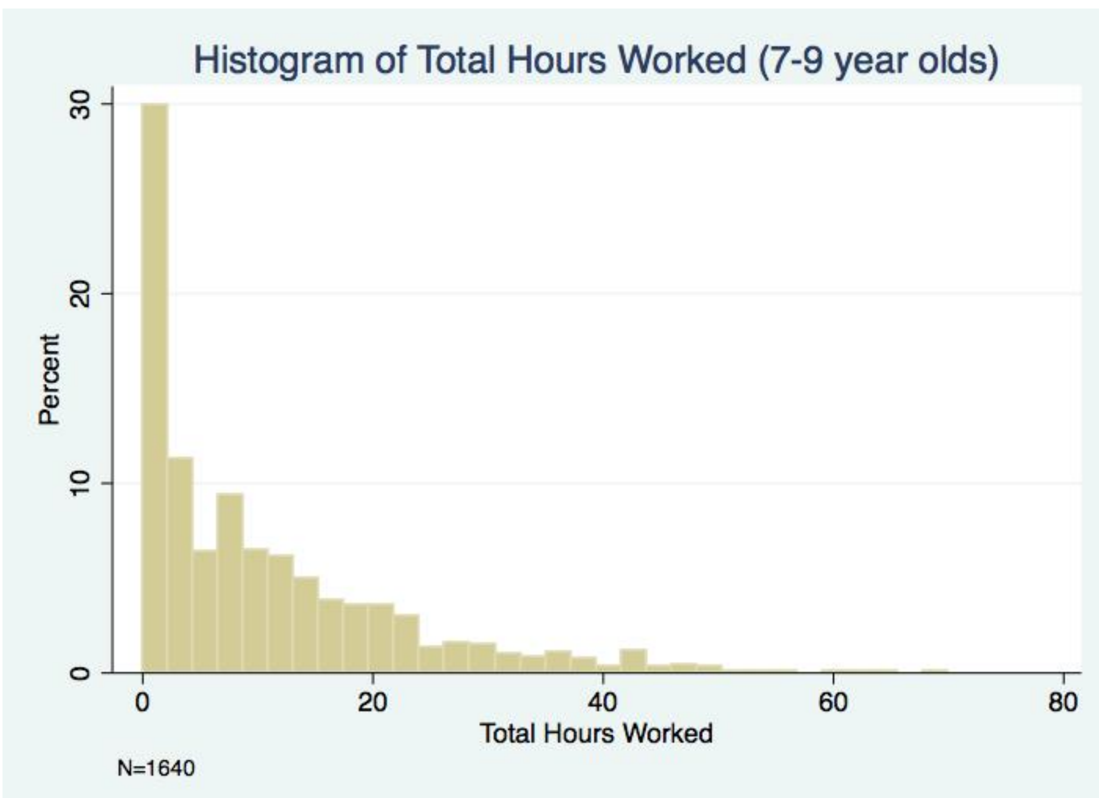


Table 9a: Fixed Effects Regressions to Check Exclusion of Lagged Rainfall from Distance (7 to 9 Year Olds)

VARIABLES	(1) Dropout	(2) Enrollment	(3) Grade minus Grade for Age
Standardized Lagged Short Rain Deviation	-0.0283	0.0468***	0.00614
	(0.0240)	(0.0156)	(0.0602)
Standardized Lagged Long Rain Deviation	0.0139	-0.0118	-0.0153
	(0.0274)	(0.0139)	(0.0345)
Standardized Lagged Dry 1 Rain Deviation	0.0353	0.00729	0.0762
	(0.0245)	(0.00978)	(0.0484)
Standardized Lagged Dry 2 Rain Deviation	-0.0151	-0.0418***	-0.128***
	(0.0200)	(0.0132)	(0.0466)
Std. School Distance Deviation X Std. Lagged Short Rain Deviation	0.00134***	-0.000522*	0.000428
	(0.000478)	(0.000267)	(0.000604)
Std. School Distance Deviation X Std. Lagged Long Rain Deviation	9.78e-05	-0.000161	-0.000244
	(0.000644)	(0.000432)	(0.000997)
Std. School Distance Deviation X Std. Lagged Dry 1 Deviation	-0.000754	0.000345	0.000281
	(0.000747)	(0.000445)	(0.00118)
Std. School Distance Deviation X Std. Lagged Dry 2 Deviation	-9.41e-05	-3.57e-05	0.000722
	(0.000389)	(0.000335)	(0.000760)
Std. School Distance Deviation	-0.00221	-0.000211	0.00853*
	(0.00501)	(0.00296)	(0.00497)
Constant	-1.869	-1.908*	11.49***
	(1.627)	(1.097)	(2.837)
Observations	417	1,691	659
R-squared	0.304	0.246	0.551

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Additional controls: age, age squared, log of real asset per capita, number of chronically ill adults, number of acutely ill adults, household composition variables, number of deaths variables, and month of interview dummies. The school distance standard deviations are from the mean cluster and wave level.

Table 9b: Joint Significance Test of "Lagged Rainfall Deviation" X "School Distance Deviation"

Dependent Variable	F-Statistics	P-Value
Dropout	5.21	0.00
Enrollment	1.52	0.19
Grade Minus Grade for Age	0.44	0.78

Table 10a: Fixed Effects Regressions to Check Exclusion of Current Rainfall from Distance (7 to 9 Year Olds)

VARIABLES	(1) Dropout	(2) Enrollment	(3) Grade minus Grade for Age
Standardized Short Rain Deviation	0.00909	-0.0507***	0.0440
	(0.0302)	(0.0146)	(0.0534)
Standardized Long Rain Deviation	-0.000206	-0.0526***	0.00112
	(0.0317)	(0.0183)	(0.0574)
Standardized Dry 1 Rain Deviation	0.00318	-0.00580	0.485***
	(0.0486)	(0.0183)	(0.131)
Standardized Dry 2 Rain Deviation	-0.0235	0.0134	-0.00928
	(0.0266)	(0.0148)	(0.0593)
Std. School Distance Deviation X Std. Short Rain Deviation	0.00156	0.000495	-0.00298
	(0.00198)	(0.000695)	(0.00326)
Std. School Distance Deviation X Std. Long Rain Deviation	-0.00269*	0.000713	-0.00296
	(0.00155)	(0.000513)	(0.00216)
Std. School Distance Deviation X Std. Dry 1 Deviation	0.00525***	0.000295	-0.00373
	(0.00183)	(0.000961)	(0.00270)
Std. School Distance Deviation X Std. Dry 2 Deviation	0.000652	-7.38e-05	0.000134
	(0.000806)	(0.000403)	(0.00135)
Std. School Distance Deviation	-0.0116**	-0.00359	0.0198**
	(0.00567)	(0.00350)	(0.00883)
Constant	-0.490	-2.007*	13.41***
	(1.475)	(1.099)	(3.229)
Observations	417	1,691	659
R-squared	0.349	0.246	0.581

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Additional controls: age, age squared, log of real asset per capita, number of chronically ill adults, number of acutely ill adults, household composition variables, number of deaths variables, and month of interview dummies. The school distance standard deviations are from the mean cluster and wave level.

Table 10b: Joint Significance Test of "Rainfall Deviation" X "School Distance Deviation"

Dependent Variable	F-Statistics	P-Value
Dropout	7.48	0.00
Enrollment	0.60	0.66
Grade Minus Grade for Age	1.83	0.12

Table 11: Mean Child Labor Hours according to the Grade Minus (Modal) Grade for Age and Age Groups

Variable	Grade - Grade for Age >= 0				Grade - Grade for Age < 0			
Age Groups	7 to 9	9 to 11	11 to 13	13 to 15	7 to 9	9 to 11	11 to 13	13 to 15
Total Hours	10.27	14.50	19.11	20.90			17.59	21.14
Std. Dev	10.30	11.14	13.01	13.03			11.93	14.02
Chores	6.81	9.06	12.16	13.38			11.21	13.10
Std. Dev	7.58	7.83	8.82	8.77			8.37	9.36
Econ	3.45	5.43	6.95	7.52			6.37	8.03
Std. Dev	5.87	6.82	8.26	8.03			7.48	8.62
N=	330	649	655	852	0	0	287	581

Table 12: Grade Minus (Modal) Grade for Age on Lagged Hours

	Child Fixed Effect		Pooled Models		Household Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE IV	FE	IV	OLS	Wave 2	Wave 3	Wave 4
Reference Mean	-0.0030		-0.0030		-0.0231	0.1409	-0.1367
Grade – Grade for Age	-0.0567***	-0.0018**	-0.1989	-0.0006	-0.0059	0.0056	0.0009
Std. Err	0.0215	0.0009	0.1601	0.0023	0.0054	0.0066	0.0079
t-stat/z-stat	-2.63	-2.02	-1.24	-0.26	-1.09	0.85	0.11
N	2334		2334		822	788	724

Table 13: Grade Minus (Modal) Grade for Age on Current Hours

	Child Fixed Effect		Pooled Models		Household Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE IV	FE	IV	OLS	Wave 1	Wave 2	Wave 3	Wave 4
Reference Mean	0.0561		0.0561		0.2583	-0.0226	0.1061	-0.1289
Grade – Grade for Age	-0.0227	0.003***	-0.0167	-0.0001	-0.0097	-0.0094	0.002	0.0024
Std. Err.	0.019	0.0009	0.023	0.0019	0.0066	0.0059	0.007	0.0093
t-stat/z-stat	-1.19	3.24	-0.73	-0.06	-1.48	-1.6	0.28	0.25
N	3354		3354		840	884	854	776

*** p<0.01, ** p<0.05, * p<0.1

Table 14: First Stage (Total Hours) Regression of Instrumental Variable Approach

	Using Current Hours		Using Lagged Hours	
	(1)	(2)	(3)	(4)
VARIABLES	No Instruments	With Instruments	No Instruments	With Instruments
Standardized Short Rain Deviation		0.118		0.332*
		(0.139)		(0.172)
Standardized Long Rain Deviation		0.188		-0.403
		(0.228)		(0.323)
Standardized Dry 1 Rain Deviation		-0.198		0.0222
		(0.219)		(0.296)
Standardized Dry 2 Rain Deviation		0.631***		0.389
		(0.219)		(0.280)
Age	6.352***	6.343***	5.358***	5.367***
	(0.691)	(0.691)	(0.917)	(0.919)
Age Squared	-0.194***	-0.193***	-0.138***	-0.138***
	(0.0319)	(0.0319)	(0.0413)	(0.0414)
Female=1, Male=0	2.432***	2.464***	2.280***	2.278***
	(0.370)	(0.370)	(0.461)	(0.461)
Log of Real Asset Per Capita in Thousands of Tanzanian Schillings	0.204	0.242	0.0560	0.0838
	(0.166)	(0.167)	(0.224)	(0.226)
Father's Baseline Education Level	-0.0906	-0.102	-0.0537	-0.0634
	(0.0632)	(0.0633)	(0.0774)	(0.0776)
Mother's Baseline Education Level	-0.0502	-0.0492	0.0577	0.0659
	(0.0691)	(0.0693)	(0.0869)	(0.0872)
Acutely Ill Adults	0.442**	0.384*	-0.108	-0.113
	(0.206)	(0.207)	(0.255)	(0.255)
Chronically Ill Adults	-0.0255	-0.122	-0.260	-0.335
	(0.312)	(0.314)	(0.412)	(0.413)
Number of Adult Females	-1.693***	-1.606***	-1.492***	-1.451***

	(0.199)	(0.202)	(0.229)	(0.231)
Number of Adult Males	-0.973***	-0.955***	-1.031***	-1.002***
	(0.186)	(0.187)	(0.218)	(0.218)
Number of Female Children under 7 years old	-0.193	-0.229	0.0220	0.0328
	(0.201)	(0.202)	(0.257)	(0.258)
Number of Male Children Under 7 years old	0.218	0.181	-0.0230	-0.0322
	(0.204)	(0.205)	(0.250)	(0.252)
Number of Female Adolescents 16 & 17 years old	-1.739***	-1.740***	-1.833***	-1.841***
	(0.350)	(0.349)	(0.450)	(0.450)
Number of Male Adolescent 16 & 17 years old	-0.937**	-0.940**	-0.646	-0.620
	(0.400)	(0.402)	(0.465)	(0.467)
Number of Female Seniors above 55 years old	0.183	0.204	0.498	0.512
	(0.344)	(0.343)	(0.449)	(0.448)
Number of Male Seniors above 55 years old	-1.075***	-1.120***	-1.579***	-1.613***
	(0.409)	(0.408)	(0.519)	(0.520)
Number of Total Female Adult Deaths (18-55)	-0.604	-0.927	3.659	3.774
	(1.840)	(1.766)	(4.763)	(4.803)
Number of Total Male Adult Deaths (18-55)	-4.927***	-4.945***	-3.031	-3.458
	(1.225)	(1.337)	(2.599)	(2.674)
Number of Total Children under 7 deaths	4.330	4.104	4.558	4.242
	(3.770)	(3.738)	(3.647)	(3.646)
Number of Total Children 7-15 deaths	-9.268***	-9.519***	-3.376	-3.177
	(2.126)	(2.107)	(2.375)	(2.366)
Number of Total Adolescents aged 16 and 17 dying	-2.500	-1.500	-11.21**	-10.61**
	(3.661)	(3.675)	(4.766)	(4.788)
Number of Total Seniors	1.354	1.347	-0.666	-0.417

>55 years old dead				
	(2.195)	(2.203)	(2.369)	(2.377)
2.month	-2.777***	-2.760***	-7.935***	-8.578***
	(0.957)	(0.965)	(1.638)	(1.669)
3.month	-3.515***	-3.761***	-6.012***	-6.368***
	(0.950)	(0.949)	(1.609)	(1.659)
4.month	-4.022***	-3.767***	-4.527***	-4.465***
	(1.086)	(1.093)	(1.682)	(1.679)
5.month	-3.909***	-3.603***	-7.302***	-7.481***
	(1.027)	(1.024)	(1.663)	(1.655)
6.month	-3.051***	-2.912***	-8.689***	-8.822***
	(0.956)	(0.956)	(1.510)	(1.509)
7.month	-0.697	-0.905	-1.979	-2.335
	(1.020)	(1.026)	(1.574)	(1.590)
8.month	-3.631***	-3.649***	-3.235**	-3.391**
	(0.917)	(0.913)	(1.545)	(1.554)
9.month	-3.192***	-3.201***	-6.863***	-7.188***
	(0.922)	(0.926)	(1.469)	(1.473)
10.month	-3.954***	-4.210***	-5.498***	-5.852***
	(0.918)	(0.923)	(1.548)	(1.571)
11.month	-2.494***	-2.346**	-7.705***	-7.625***
	(0.911)	(0.914)	(1.507)	(1.500)
12.month	0.789	0.796	-7.272***	-7.414***
	(0.997)	(0.991)	(1.518)	(1.512)
Constant	-22.80***	-22.79***	-15.99***	-15.85***
	(3.674)	(3.675)	(5.111)	(5.105)
Observations	5,076	5,076	3,244	3,244
R-squared	0.188	0.190	0.204	0.206
Joint Significance of Instruments (P-Value)		**0.0046**		**0.1562**

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1