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Child Labour And School Attendance: Evidence from Selection on Observed and Unobserved  
Variables in Zambia

A Dissertation

submitted to the Commerce Faculty of the  
University of Cape Town  
in partial fulfillment of the  
requirements for the degree of  
Master of Commerce

in  
The School of Economics

by  
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February, 2010

## Declaration

I declare that this thesis hereby submitted for the Masters of Commerce degree in Economics at the University of Cape Town is my own effort and has not been previously submitted anywhere else. I also acknowledge that plagiarism is an offence and therefore I have quoted all sources that I have used in this thesis.

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## Acknowledgements

I would like to express my profound gratitude to all those who helped me during the preparation of this thesis and also during my course-work period. It would have been next to impossible without the guidance and support from

- Professor Murray Leibbrandt who took time to supervise this dissertation and through the Hewlett Foundation and Population Reference Bureau funded my studies. I am indebted to your generosity as well as insightful and incisive comments which made me realize that econometrics is and should be a servant to social science.
- Chrispin Mphuka and his family, Mashekwa Maboshe, Grieve Chelwa, Mhebuba Shifa and many other friends in Cape Town, who supported me in many ways during my studies.
- My family who endured my long absence from home. I offer my regards and blessings to you all. To little Cape, Ambuya couldn't hide her emotions anymore

Lastly I owe it all to my Lord. Thanks be to God

*I dedicate this dissertation to my two surviving grandmothers, Mizinala Nalwimba Simumba and Faidess Phiri Banda*

## Abstract

Although the determinants of child labour and school attendance are well established in the literature, the causal effect of child labour on school attendance is largely unexplored owing in part to econometric challenges. The difficulty in finding a valid and strong instrument for child labour, which is argued to be interdependent with school attendance, is one such impediment. Recognizing this difficulty and the fact that children in child labour differ from their counterparts who are not in child labour along an array of observed and unobserved characteristics, I proceed along an alternative path in this paper. I examine the causal effect of long run child labour on children current school attendance using a novel estimation method that assumes that the amount of selection on observed variables closely approximates the amount of selection on unobservables. Using data for children between 5 and 17 years in Zambia, empirical results show that child labour has a significant negative effect on the probability of school attendance. The point estimate is also robust to unobserved variables. Results also show that children who participate in child labour are relatively older, hardly live with their mothers, mostly live in rural areas and are found in households where parents or household heads are relatively older and spent less time in school.

# 1 Introduction

One of the negative consequences of child labour often cited in calls for its abolishment is that child labour leads to low school attendance among children. For example, when children participate full time in the labour market, effectively child labour displaces school attendance. But in the case where children supply their labour on a part time basis, child labour can actually lead to improved school attendance by improving households' subsistence income. This is especially plausible when child labour is an outcome of absolute poverty like in many less developed countries (Basu & Van 1998). The question of which effect dominates the other is ambiguous in theory and remains an empirical matter.

A vast empirical literature analyzes the relationship between child labour and school attendance (e.g. Akabayashi 1999, Canagarajah & Coulombe 1997, Nielsen 1998, Ganglmair 2006). However this literature examines a correlation and not a causal effect. Examining the correlation between child labour and school attendance at the household level does not take into account the non-random assignment of child labour typically observed in household survey data. Households that send their children to work often differ from those that do not along an array of factors such as wealth, education, occupation, regional location that are observed to the econometrician and along factors such as social networks, concern for children, beliefs about children, and the ability of children that are not unobserved. Therefore if households send their least(most) motivated children to work, this can generate a negative(positive) correlation between child labour and school attendance purely because of selection bias (Beegle, Dehejia & Gatti 2009).

Generally, finding a causal effect of child labour on children school attendance is challenging due to absent experimental data because child labour is perceived to be unethical worldwide. In addition, when deciding whether to send a child into child labour or not, almost every household decision maker including some children as well, use some information on unobserved factors that are also likely to influence school attendance at the same time. Ignoring this potential endogeneity of child labour arising from the joint determination of child labour and schooling decision can lead to inconsistent estimates of the effect on child labour on school attendance(see Greene 2003, Wooldridge 2002).

Instrumental variables (IV) estimation has been widely used in the literature in order to account for bias due to endogeneity of child labour based on non-experimental data which is known as observational data in the literature on causality. This approach involves innovative construction of variables that serve as instruments for child labour. In studies that use cross section data, the instrumental variable is included in the child labour equation but excluded in the school attendance equation. This exclusion restriction assumes that variation in the instrument is orthogonal to innovations that affect school attendance. A variable that serves as an instrument . gives the coefficient

on child labour a causal interpretation. This method is popular in studies that use panel data because panel data usually contains rich and strong prior information from which good and valid instruments are found. In the absence of panel data or some other rich augmenting data, it is difficult to find instruments which is usually the case with cross section data. In almost all respects, observed characteristics that determine child labour such as demographic composition of the household, per capita non-child income, education attainment of household head and regional location of the household, also influence the household decision to send a child into school directly. Therefore it is difficult to justify why any of these variables should be excluded in the school attendance equation.

The propensity score matching and reweighting method is another approach which has been used in the literature besides the instrumental variable technique. This method uses the counterfactual approach to causality whereby the effect of child labour on school attendance is found as the difference between the amount of current school attendance for children in child labour and the one that could have resulted if child labourers never participated in child labour. Although this method avoids the need to search for child labour instruments, its major drawback is that it assumes away selection into child labour based on unobserved factors. Almost every household decision maker, who include some children as well, use some information on the ability of the children, society norms and religious beliefs when deciding whether to send a child into child labour or not. Information on these variables is not collected in household surveys and therefore remains unknown to the econometrician. Ignoring the role of unobserved information altogether can lead to an estimate of child labour that is highly biased, inconsistent and inefficient because some useful piece of information about child labour is omitted altogether . In addition Altonji, Elder & Taber (2008), Vytlacil, Bhattacharya & Shaikh (2008) and Li, Racine & Wooldridge (2008) propose using new methods to study causal effects because they are skeptical about results from propensity score matching and reweighting method because it assumes away selection on unobserved factors.

Recognizing the difficulty in finding credible instruments and the effect of selection bias of child labour from both observed and unobserved factors, I proceed along an alternative path. In this paper I estimate the causal effect of child labour on school attendance in the absence of a valid exclusion restriction by appealing to a novel technique developed in ?. Under this method the point estimate that captures the effect of child labour on school attendance is obtained by assuming that the amount of selection into child labour based on observed factors closely approximates the amount from unobserved factors. The attempt to incorporate the effect of unobservables in the selection process of child labour is an important endeavour because it leads to a better estimate of the child labour which plausibly represents a causal effect and not a mere correlation. Therefore this paper contributes some empirical evidence in the absence of panel data, strong prior

information and an instrument or a valid exclusion restriction for child labour.

Empirical results shows that child labour has a significant negative effect on the probability of school attendance. Child labour has the largest negative effect on the probability of school attendance among children who live in rural areas. The incidence of child labour is lowest at less than four percent in households that have at least one adult member who is occupied in a salaried job outside the household. In this subsample, children who don't participate in child labour and never attend school at the same time, dominate the number of children who only participate in child labour and those who combine child labour and school attendance at all ages. Systematic differences in the mean of observed characteristics between child labourers and non-child labourers shows that children in child labour are older, stay with relatively older household heads who poses less education and about eighty seven percent of children in child labour reside in rural areas.

The rest of the paper is organized as follows: Section 2 presents a short review of the vast literature on child labour and school attendance. It specifically looks at studies that focus on the causal effect of child labour on children school attendance. Section 3 briefly explains the survey design and defines all the variables. It also presents some exploratory analyses of the data and a sensitivity analysis of child labour estimates to various assumptions about the strength of the relationship between unobserved factors of child labour and the ones for school attendance. Section 4 outlines the empirical model that estimates the effect of child labour by taking into account selection of child labour based on both observed and unobserved variables. The results from the empirical model are reported and discussed in Section 5. Section 6 concludes the paper.

## 2 Literature Review

A vast empirical literature on the relationship between child labour and school attendance shows that child labour has a trade-off effect on children school attendance (e.g. Akabayashi 1999, Canagarajah & Coulombe 1997, Nielsen 1998, Ganglmair 2006). This result is based on the negative relationship between errors from the child labour and school attendance equations estimated in a standard bivariate probit model. Because the standard bivariate probit model does not explicitly introduce a child labour variable as an explanatory variable in the school attendance equation (see Greene 2003), the trade-off literature is appreciably regarded as a correlational analysis rather than a causal analysis. But as noted by Beegle et al. (2009), correlation analysis in the presence of selection bias into child labour may depict a relationship that is purely caused by selection bias. Nonetheless the value of the correlation coefficient has been shown to vary across countries, geographical locations and the gender of children (Ganglmair, 2005 provides a useful summary on page 27). Since this paper is focused on examining the casual effect

of child labour on children school attendance, this section proceeds with a short review of a growing number of studies that seek to establish the causal effect of child labour on school attendance.

## 2.1 International literature

Cavalier (2002) uses the propensity score matching and reweighting method and finds that child labour has a significant negative effect on schooling in Brazil. Her study is based on data from a rotating panel collected in two waves. Beegle et al. (2009) also find that child labour has a significant negative effect on school attendance, among other child outcomes in rural Vietnam. They exploit exogenous variation in rice prices to identify the causal effect of child labour from panel data of 8 -13 year old children collected between 1993 and 1998. In another study of rural Tanzania, Beegle, Dehejia, Gatti & Krutikova (2008) finds that when a boy spends 5.7 hours in child labour in the first wave, ten years later he has lost approximately one year of schooling. Among girls, this effect is not observed except that child labour increase the likelihood that girls marry young.

Two other notable studies that use instruments and exclusion restrictions to infer the causal effect of child labour on school attendance are Ray & Lancaster (2003) and Boozer & Sun (2001). In Ray & Lancaster (2003), incomes, assets and infrastructure (telephone, water and electricity) are used as instruments or excluded variables in a two stage estimation method which they apply to seven countries. They too find that child labour has a negative effect on school attendance. Boozer & Sun (2001) use hours of child work in Ghana, a variable that is rarely available or properly collected in less developing countries. They find that one hour rise in child labour leads to twenty three minutes decline in contemporaneous school attendance. Regional variation of rainfall patterns is used as an instrument for child labour.

In this paper, I contribute beyond these studies empirical evidence of the causal effect of child labour on school attendance in the absence of an instrument or exclusion restriction for child labour and also evidence in a country that lacks panel data.

## 2.2 Zambian literature

There are only two papers that consider child labour and school attendance in Zambia, namely Jensen & Nielsen (1997) and Nielsen (1998). Jensen & Nielsen (1997) seek to find factors that determine each of child labour and school attendance. Their results show that both economic and sociological variables are important for the choice between child labour and school attendance. Using a random effects logit model with unobserved factors assumed to be homogenous at household level, they find that both child labour and school attendance are significantly affected by poverty, among others, based on data from priority survey II conducted in 1993.

A serious limitation of Jensen & Nielsen (1997) is that it incorrectly captures child labour because it assumes that child labour and school attendance are mutually exclusive. Since a significant proportion of children in Zambia combine school and child labour at the same time with another significant proportion neither in child labour nor school, it is incorrect to measure child labour as the inverse of school attendance. In this paper I explicitly take into account all the four discrete outcomes that emerge when child labour and school attendance are interacted. In addition, I use data that is more recent.

Nielsen (1998) examines the joint determination of child labour and school attendance within a standard bivariate probit model based on data from the poverty priority survey of 1993 augmented with data from the community survey on education and infrastructure also conducted in 1993. Her findings show that child labour has a trade-off effect on school attendance in a model that controls for income effects. She uses expenditure per adult equivalent to capture income effects and instruments it using the education, age and square of age variables for the head of the household. The correlation coefficient between unobserved factors that affect school attendance outcome and the ones that determine child labour is -0.63 for the whole sample and -0.65 for the rural sub-sample. This means that unobservables of child labour and school attendance are more negatively correlated in the rural sample than in the national sample. Her results also show that child labour is insensitive to income changes in the presence of observed control factors. Unlike Nielsen (1998), this paper attempts to move beyond these correlations and to estimate the causal effect of child labour on school attendance.

## 3 Preliminary Data Analysis of Child Labour and School Attendance

### 3.1 Survey design and data

I use data from the Zambia Child Labour survey that was conducted in 1999 by the Central Statistical Office under the auspices of the International Labour Organization's Statistical Information and Monitoring Programme on Child Labour (SIMPOC). This survey used a two stage stratified cluster sampling procedure. In the first stage primary sampling units (standard enumerators areas) were sampled from eighteen strata created by subdividing the nation's nine provinces into rural and urban. Three hundred and sixty primary units were then selected from a total of 13,000. In the second stage all households in a selected primary unit were listed and stratified further before being selected. In urban areas, households were stratified into three categories. The first category comprised households that had at least one paid child worker while households with unpaid child workers formed the second category. Households with no child workers

were grouped into the third category. In rural areas households were further stratified on the basis of their scale of agricultural activity.

A proportionate allocation of households into the sample based on probability proportionate to size failed to deliver sensible estimates in three provinces. As a result, a modified rule known as the square root method of the probability proportionate to size method was adopted leading to a total sample of 8000 households proportionally distributed between rural and urban areas based on their population size. A detailed discussion of the sampling procedures is provided in Zambia Child Labour Country Report published in 1999.

Data collected in the child labour survey contains useful information on demographic background, schooling profile, labour force participation, orphanhood status and geographical location of the household for all members aged five years and above. The data also contains a sampling weight variable which is computed as the inverse of first and second stage selection probability for each observation. Unless noted otherwise, estimations in this paper use this weight variable to account for representativity of the sample. However the variance and corresponding standard errors estimated in this paper only account for the effect of clustering and exclude the effect of stratification in order to reduce the complexity of computations. Because stratification leads to some gain in precision whereas clustering worsens precision of estimates, the variance and standard errors in this paper represent a conservative scenario.

### 3.2 Measurement of child labour and school attendance

I define child labour as a dichotomous variable that equals one if the main economic activity in the last twelve months of any individual aged between five and seventeen years, is working for or without remuneration in any formal or informal enterprise, and zero otherwise. Main economic activities that were recorded in rural areas are linked to farm labour such as crop cultivation, livestock tending, craftsmanship and charcoal burning. In urban areas prominent activities included street hawking, petty trading, car washing, artisan assistant, stone crushing and domestic servant. Non-economic activities in own home such as housekeeping are not categorized as child labour under this variable. Although this variable is prone to recall lapse, it possess a peculiar advantage of capturing long run child labour. Interalia, this form of child labour underlies the dynastic poverty trap which is characterized by a vicious sequence of child labourers becoming less educated parents and giving birth to children who grow up doing child labour with low educational attainment (see Tzannatos & Basu 2003). If child labour is measured from a parent or head of households' response, it can be understated if parents feel ashamed of child labour. Also identifying child labour based on children responses is problematic and usually leads to overstatement largely due to misunderstanding of what constitutes child labour.

School attendance is also measured as a dichotomous variable which is equal to one if a child currently attends school and zero otherwise. In effect, this paper examines the effect of long run child labour (at one year horizon) on current and not contemporaneous school attendance.

Observations with missing values on school attendance, child labour or any control variable used in this paper are dropped. As a result I first estimate the model without the income variable and later include it because it contains a lot of missing values and I can't find another income variable besides it that is plausibly exogenous. Without income, the total effective sample size consists of 6229 children belonging to 332 primary units or clusters while with the income variable, the sample consists of 3024 children. I also estimate the model on a subsample of children who reside in rural areas because eighty seven percent of all working children live in rural areas. The proportion of children who live in rural areas in the total sample is 46% which translates into 2888 children

### 3.3 Control variables

Most studies on child labour and school attendance that were reviewed in the previous section, use a standard set of variables to capture respectively, the influence of demographic factors, parental effects, economic occupation and marital status of household head, household income effects and geographical location of the household. The control variables that I consider in this paper are in line with this standard set and can also be found in Jensen & Nielsen (1997), Nielsen (1998) and Cavalier (2002). However I restrict attention to variables that plausibly take values or are observed before school attendance or child labour is known (i.e. exogenous covariates). Exogeneity of control variables helps to interpret the coefficient on child labour as showing a causal effect. This requirement precludes the inclusion of household expenses on children education which Jensen & Nielsen (1997) and Nielsen (1998) use as a covariate because it is directly influenced by school attendance and child labour respectively. A better variable which can be used to capture the effect of direct schooling costs is school user-fees that are often set by school authorities as long as they are determined independent of household child labour or school attendance outcomes. Unfortunately the child labour survey did not collect information on community level variables which explains why I do not control for community level effects as done in other studies. The requirement of covariate exogeneity also explains why the effect of income is captured only by salaries of household adult members that are earned outside the household. These wages are determined by employers independent of child labour and school attendance outcomes in the employees household.

I also use variables of the head of household because available data only identifies the household head and not the parent of a child. Nonetheless children were also asked to indicate whether they live with their mother and or their father under the orphanhood

module. The two indicator variables namely, live with mother and live with father, are measured based on the response categories on this question. Therefore these variables can also be interpreted as proxies for orphanhood although the main purpose for including them is to capture biological parental effects. A priori it can be argued that children who don't stay with their biological parents are vulnerable to child labour and face a hazard of not attending school.

In Zambia, when children commence teenagehood, they are expected to quickly learn survival skills before they assume adulthood which often starts five years after thirteen years (at eighteen years). In addition, the predominant young population structure with a median age of sixteen years caused by low life expectancy (see 2000 Census of Population and Housing Report?), entails that children assume responsibilities within a short period after they grow past the age of 12 years. Therefore age is included because it also matters for child labour. Like Nielsen (1998), I include a square of age in order to capture its non-linear pattern on child labour (see Figure 1).

The sex ratio and child rank variables capture the exogenous effects of sibling composition and birth order respectively, that have been shown to matter for child labour and school attendance by Edmonds (2006) and Danmert (2010). For example, in households that have a fairly balanced number of children in terms of both gender and age, boys often specialize in market work while girls usually specialize in domestic work. Also in settings of absolute poverty, older children usually fend for their household's livelihood while young siblings often attend school. Although total household size is another key determinant of child labour which is plausibly exogenous, I omit it due to collinearity problem with boy and child ratio variables when estimating the model. Table 1 presents the variable dictionary of all control variables used in this paper.

Table 1: Variable Dictionary

<u>Variable</u>	<u>Definition</u>
<i>Demographic characteristics</i>	
Age	Age of a child in completed years
Age <sup>e</sup> <b>Square of age</b>	
Boy	Indicator variable =1 if the gender of the child is male
Sex Ratio	Ratio of males to females in the household
Sex Ratio <sup>2</sup> <b>Square of sex ratio</b>	
Child Ratio	Ratio of children to adults in the household
Child Rank	Age rank of a child among children in the Household
Head's Age	Age of household head in completed years
<i>Parental effects</i>	
Live with Mother	Indicator variable =1 if a child lives with the biological mother, 0 otherwise
Live with Father	Indicator variable =1 if a child lives with the biological father, 0 otherwise
Head's Education	Highest education level of the head of the household in completed years
<i>Marital status of household head</i>	
Marital Status	Household head marital status defined by five indicator variables namely single,married, separated, divorced and widowed
<i>Economic sector of household head</i>	
Economic Sector	Employment sector of household head defined by ten indicator variables; self employed, parastatal, private sector, NCO/embassy, domestic servant, unpaid family worker, central or local government, employer,other
<i>Income effects</i>	
Per capita income	Logarithm of the quotient of total adult salaries by total household size
<i>Regional/residential location</i>	
Rural	Indicator variable =1 if a child resides in a rural designated area
Province	Nine indicator variables representing the nine provinces of Zambia

### 3.4 Sample characteristics

When child labour is interacted with school attendance, they produce a set that contains four mutually exclusive discrete outcomes,  $\{(1,1), (1,0), (0,1), (0,0)\}$ , with each element in the set corresponding to children who either combine child labour and schooling at the same time or only work or attend school only or neither attend school nor work hereafter called idle children, respectively. In Table 2 below, I report both weighted and unweighted percentage composition of the four discrete outcome categories for the total effective total sample which consists of 6229 individuals. Without sample weights, 10.3 percent of all children in the sample participate in child labour but after observations are

weighted using sampling weights, the figure rises to 12.7 percent. Eighty seven percent of all children attend school. This is consistent with existing evidence provided by UNESCO and Ministry of Education (?). Out of all children who participate in child labour, 34.6 percent also attend school compared to 90 percent of all children who do not participate in child labour. If children were randomly assigned into child labour, the magnitude of this difference is sufficient to conclude that child labour leads to low school attendance among children. Because child labour is not randomly assigned in observational survey designs which was used to collect the data that I use in this paper, the presence of selection bias renders this interpretation naive and invalid.

Table 2: Categorical Percentages of Child Labour and School Attendance

<u>Weighted Sample</u>				<u>Unweighted sample</u>			
<u>Attend School</u>			<u>Child Labour</u>	<u>Attend School</u>			<u>Child Labour</u>
	No	Yes	<b>Total</b>		No	Yes	<b>Total</b>
No	8	8.3	16.3	No	6.9	7.1	14
Yes	79.3	4.4	83.7	Yes	82.8	3.2	86
<b>Total</b>	<b>87.3</b>	<b>12.7</b>	<b>100</b>	<b>Total</b>	<b>89.7</b>	<b>10.3</b>	<b>100</b>

Source: Own calculations using SIMPOC data

Sample size(N) = 6229

In Figure 1, I show the distribution of the four discrete outcomes by age. Each point on the graph represents the proportion of children in a given outcome group to the total number of children at that age. The school attendance only category dominates at every age. Between ages five and seven, the number of idle children declines substantially as they enroll into school which results in the school attendance only outcome group picking up quite sharply. The child labour only outcome group is second largest after school attendance when children grow past the twelfth age and rises steadily up to age seventeen. Between five and seven years most children belong to school attendance only and idle categories. Beginning from 10 years, the school attendance only outcome declines gradually leading to child labour and school attendance category to rise until the twelfth age. But after the twelfth age further decline in school attendance leads to the number of children who combine school and child labour to also decline. Consequently child labour only and idle children categories pick up steadily although most children end up participating into child labour only. The decline in school attendance before the twelfth or thirteenth age can be attributed to natural attrition. But beyond these ages some amount of the decline can be attributed to failure of school examinations which commence at the end of grade seven. The pupils also take another exam at the end of grade nine when most of them are either fourteen or fifteen years. Because a significant proportion of children who fail grade seven exams may completely drop out of school, they are prone to end up as child labourers which partly explains the significant rise in child labour after

age fourteen besides the fact that child labour rises with responsibilities which come with growing up.

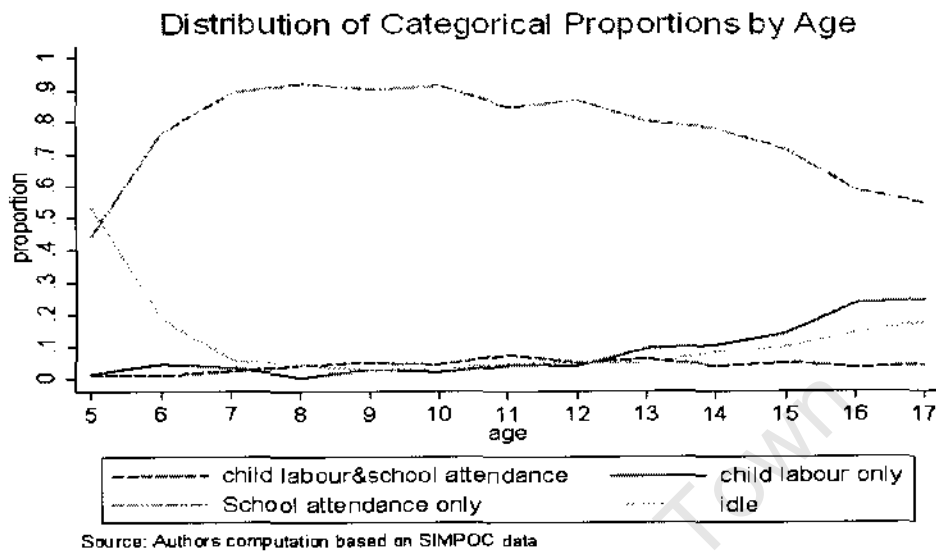


Figure 1: Age Distribution of Weighted Discrete outcomes

### 3.5 Characteristics of children by child labour status

In Table 3, I report the weighted means by child labour status for school attendance and all control variables except for the sector of employment for the household head and province dummies for the total sample. This table gives a descriptive comparison of the difference between means for key observed variables between children who participate in child labour and their counterparts who don't work. Children in child labour are far less likely to attend school than their counterparts who do not participate in child labour (34% against 91%) leading to a significant difference of 56 percentage points in their mean values. In terms of mean age, children in child labour are relatively older although no significant difference exists in terms of their gender composition. A higher age rank for children in child labour reinforces the observation that child labourers are relatively older or were born much earlier. Parents or heads of households who spent less years in school tend to send their children into labour activities as opposed to parents who spent relatively more time in education. This disparity if sustained across generations threatens the emergence of a dynastic poverty trap.

Children in child labour also come from households whose heads are relatively older when compared to head persons of households that do not have children in child labour. The marital status of the households' heads is very similar between children regardless of whether they participate in child labour or not. Out of the total number of all children who don't participate in child labour, fifty four percent live in rural areas.

The majority of children (87%) who participate in child labour reside in rural based compared with only 13% who live in urban areas. This result is not surprising given that the main economic activity in rural areas is labour intensive agriculture. Widespread child labour in rural areas can be attributed to factors such as credit constraints and imperfect mobility of labour that are responsible for the observation that land rich households in rural Africa tend to have pronounced child labour (Bhalotra & Heady 2003). Jensen & Nielsen (1997) also note that widespread absolute poverty in rural areas is a key determinant of child labour. In this paper I also conduct separate estimations for children that live in rural areas.

The differences in mean values of variables by child labour status in the rural subsample also follow a pattern that is similar to the one observed in the total sample in terms of the statistical significance from zero except for the widowed marital status variable. In the rural subsample relatively more child labourers live in households whose heads or parents lost a spouse due to death when compared to children who are not child labourers at ten percent significance level.

However descriptive evidence on differences in mean values of observed variables for children in the income subsample shows quite different results on household heads age and education variables. The magnitude of the difference in means on these variables are statistically zero, unlike in the total sample and the rural subsample. The difference on the log of per capita income variable between children in child labour and their counterparts who are not in child labour is also insignificant. Nonetheless the coefficients on age, school and child rank are significantly different from zero.

In short, the descriptive differences in the mean characteristics by child labour status indicate notable systematic differences in some observed variables between children in child labour and their counterparts who don't participate in child labour. This information provides some evidence that some amount of selection into child labour is based on observed variables.

Table 3: Weighted Difference in Means by Child Labour Status

Variable	Child Labour =0	Child Labour=1	Difference
School attendance	0.91	0.34	0.56 [0.07]***
Boy	0.50	0.48	0.02 [0.03]
Age	11.48	13.58	-2.10 [0.32]***
Square of age	142.07	193.17	-51.10 [8.04]***
Sex ratio	1.29	1.28	0.01 [0.06]
Square of Sex ratio	2.68	2.49	0.20 [0.27]
Child ratio	0.49	0.49	0.00 [0.01]
Age rank	3.81	5.15	-1.34 [0.61]**
Live with mother	0.87	0.83	0.04 [0.02]***
Live with father	0.82	0.76	0.07 [0.03]**
H/head education	9.28	7.57	1.71 [0.20]***
Married	0.92	0.92	0.00 [0.02]
Separated	0.01	0.01	0.00 [0.00]
Divorced	0.04	0.04	0.00 [0.01]
Widowed	0.01	0.02	-0.01 [0.01]
H/head age	44.04	46.54	-2.49 [0.71]***
Rural	0.54	0.87	-0.33 [0.04]***

Note: \*\*\* indicates significance at 1%; \*\* at 5%; and, \* at 10% levels  
clustered standard errors reported in brackets

### 3.6 A sensitivity analysis

Before I proceed to the methodology of this paper, it is useful to set a discussion on how the causal estimate of child labour changes when the assumption regarding the relationship between unobserved factors for child labour and for school attendance is changed. Since unobserved factors are not observed by definition, any attempt to incorporate them in any empirical selectivity model entails making either implicit or explicit assumptions about their magnitude. I conduct a sensitivity exercise using a recursive bivariate probit model that is specified as

$$(3.4.1) \quad SCH = I(\alpha CH + X'\gamma + \varepsilon > 0)$$

$$(3.4.2) \quad CH = I(X'\beta + u > 0)$$

$$\begin{bmatrix} u \\ \varepsilon \end{bmatrix} \sim N \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right)$$

where  $CH$  is the child labour indicator variable and  $SCH$  captures school attendance as a function of a linear index.

In this model, various assumptions about the selection process or endogeneity of child labour can be incorporated into the model as constraints on the value of the correlation

coefficient between the error terms. The correlation coefficient in this model captures the correlation between unobserved factors that influence child labour and the ones that affect school attendance. Another major advantage of the recursive bivariate model is that it not only captures child labour and school attendance as joint decisions but it also measures the unidirectional causality of child labour on school attendance at the same time.

The coefficient on child labour,  $\alpha$  and its marginal effect are parametrically identified based on the bivariate normal distribution even if the vector of control variables,  $X$  is the same in both the school attendance and child labour equations (see Wilde 2000). However, results from this model in the absence of all instrument for child labour or a valid exclusion restriction are not trusted among empirical researchers. Since I don't possess a valid instrument and the model requires only one restriction to deliver credible estimates of child labour, I proceed by fixing the values of the correlation coefficient,  $\rho$  and observe how the value of  $\alpha$  changes. Rosenbaum & Rubin (1983) and Rosenbaum (2002) provide examples of this type of sensitivity analysis of causal estimates to confounding effects emanating from unobservables. Because the true value of the correlation coefficient is not known in reality, I experiment with values of  $\rho$  beginning from -0.8 and successively varying them by 0.1 increments up to 0. I choose the negative values of  $\rho$  because Nielsen (1998) and many other studies summarized by Ganglmair (2006) find that  $\rho$  is negative which they use to conclude that child labour has a trade-off effect on school attendance. I omit values of  $\rho$  below -0.8 because stata cannot generate feasible initial values to optimize the likelihood function. In Figure 2, I report estimated coefficients of child labour alongside their approximate 95 percent confidence intervals based on clustered standard errors in the upper panel while marginal effects with their approximate 95 percent confidence intervals are shown in the lower panel.

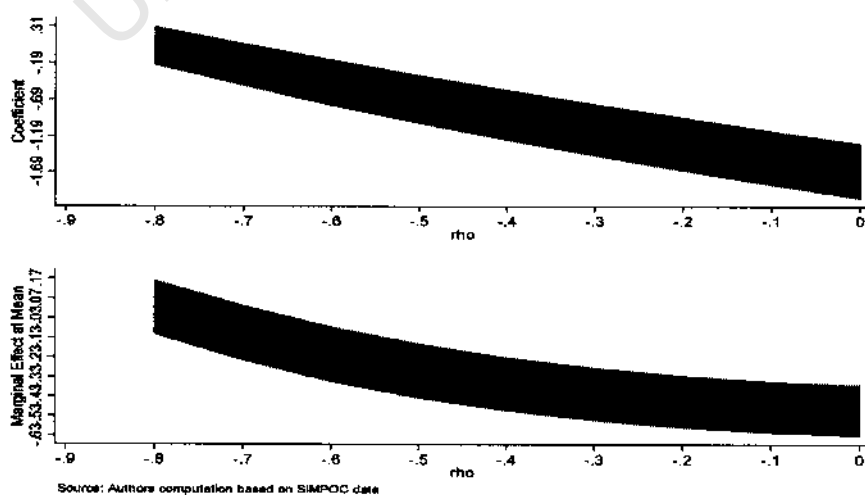


Figure 2: Sensitivity of Coefficients(a) and Marginal Effects(b) to Various values of

## Correlation Coefficients with Approximate 95% Confidence Intervals

When the correlation coefficient is assumed to be zero, the joint normality assumption implies that child labour and school attendance are independent choices once observed factors are taken into account. This means that child labour is no longer endogenous so that its effect on school attendance can be obtained from a univariate probit regression. Under this assumption child labour has the largest negative value on the probability of school attendance. Because magnitudes of coefficients from non-linear models such as bivariate probit do not lend themselves easily to interpretation, I report marginal effects that are computed at the mean value of child labour and control variables. The marginal effect of child labour at the correlation coefficient value of zero is equal to -0.50 which is also the largest negative effect in the whole range.

As the correlation coefficient approaches negative one, meaning a rising and strong negative relationship between unobservables that determine child labour and the ones that affect school attendance, estimated coefficient values for child labour and its corresponding marginal effects decline monotonically towards zero in terms of absolute values. This depicts a declining negative effect of child labour on school attendance. At the correlation coefficient of about -0.8, the qualitative effect of child labour on school attendance reverses sign from negative to positive although its statistically zero. The key point from this result is that strong selection on unobservables is required to explain away the negative effect of child labour on children school attendance. In the next section, I outline a model that endeavours to explicitly account for some amount of selection on unobservables in estimating the causal effect of child labour on school attendance

## 4 Methodology

### 4.1 A model of joint decisions with selection bias

Let school attendance be determined by a linear unobserved utility function which depends on child labour and other observed and unobserved variables, so that a child actually attends school when utility is positive. Then I can specify an empirical model of the form

$$(4.1.1) \quad SCH^* = \alpha CH + W'\Gamma \quad \text{and} \quad SCH = I(SCH^* > 0)$$

where  $CH$  is a child labour indicator variable,  $SCH^*$  is a continuous unobserved school attendance variable,  $\alpha$  is a parameter that captures the causal impact of child labour on latent school attendance and  $W$  is a vector of all observed and unobserved variables in the universe that determine school attendance besides child labour.

When I restrict attention to variables that I can control for in the data (explanatory variables) that are plausibly not correlated with unobserved variables, 4.1.1 can be rewritten as

$$(4.1.2) \quad SCH^* = \alpha CH + X'\gamma + \varepsilon$$

where  $X$  is a vector of observed variables while  $e$  is a vector of unobserved variables and are defined to satisfy  $cov(X, e) = 0$  which is called the exogeneity condition in econometrics.

If child labour is also not correlated with unobserved factors in the  $\varepsilon$  vector, then it is sufficient to estimate the causal effect of child labour on the probability of school attendance using a univariate probit regression of equation 4.1.2. But since the theoretical argument that child labour is jointly determined with the school attendance is compelling and the presence of selection on unobservables, univariate probit regression of school attendance on child labour can yield estimates that are highly biased and inconsistent (see Greene 2003, Wooldridge 2002). As a way of addressing these pitfalls, I proceed as follows; Consider an indicator variable for child labour given by  $CH = I(CH^* > 0)$ . A linear projection of  $CH^*$  onto  $X'\gamma$  and  $e$  in 4.1.2 yields

$$(4.1.3) \quad \text{proj}(CH^* | X'\gamma, \varepsilon) = \phi_0 + \phi_{X'\gamma} X'\gamma + \phi_\varepsilon \varepsilon$$

where the  $\phi$ 's are constants of projection.

Equation 4.1.3 is the selection equation of child labour through its latent or underlying utility variable. It captures the idea that a household or any decision maker, makes the decision about child labour using use some amount of information that is observed in the data which I outlined in the control variables and some other information that is not observed in the survey such as children's ability, norms, beliefs and optimization errors. Therefore any attempts to quantify the magnitude of unobserved information in modelling the child labour selection process requires assumptions which can be explicit or implicit in nature. In this paper, I assume, as in ?, that the amount of selection into child labour based on observed variables closely approximate the amount of selection from unobserved variables which means  $O_{X,\varepsilon} = 4_E$  in equation 4.1.3. I will refer to this as the symmetry condition in the rest of the paper. Studies that assume away selection on observables like Cavalier (2002) assume that  $(i_e = 0$  which is also the case for univariate probit estimates.

To capture joint determination of child labour and school attendance, equation 4.1.2 and equation 4.1.3 are reformulated into a recursive bivariate probit model outlined in equation 3.4.1 and 3.4.2 respectively. ? show that the symmetry condition can be operationalized in the recursive bivariate probit model by imposing the condition

Condition 1

$$\rho = \frac{Cov(X'\beta, X'\gamma)}{Var(X'\gamma)}$$

## 4.2 Informal robustness assessment

Information about selection on observed factors can be informally used to provide a guide as to how large the relative amount of selection from unobservables is required to be to explain away the whole child labour effect on school attendance. If it requires only a relatively small amount of selection on unobserved variables to explain the causal estimate of child labour, then the estimate is sensitive to unobserved factors and probably depicting an incorrect effect.

The equality of normalized amount of selection on unobservables to normalized amount of selection on observed factors can be expressed as:

$$(4.2.1) \quad \frac{E(\varepsilon|CH=1) - E(\varepsilon|CH=0)}{Var(\varepsilon)} = \frac{E(X'\gamma|CH=1) - EX'\gamma(\varepsilon|CH=0)}{Var(X'\gamma)}$$

where equality follows from the symmetry condition.

This expression entails that the relationship between child labour status of children and the mean distribution of the index of unobserved factors that determine school attendance in its variance units is the same as the one between child labour status and observed factors. Based on 4.2.1 we can assess the strength of the evidence for child labour effect by asking how large the quantity on the left side of expression 4.2.1 must be relative to the quantity on the right side to explain the whole a estimate under the null hypothesis that a is zero.

A simple way to estimate the quantities in 4.2.1 is to treat school attendance and child labour as though they are continuous variables so that expression 4.2.1 is equivalent to

$$(4.2.2) \quad \frac{Cov(CH, \varepsilon)}{Var(\varepsilon)} = \frac{Cov(CH, X'\gamma)}{Var(X'\gamma)}$$

The continuous child labour variable can now be expressed as a linear sum of its predicted value plus its residuals,  $CH = X'\hat{\beta} + u$ . Letting the latent school attendance variable represent continuous school attendance, equation 4.1.2 can be re-arranged as

$$(4.2.3) \quad SCH^* = \alpha\hat{u} + X'[\gamma + \alpha\hat{\beta}] + \varepsilon$$

Because the results apply only in large samples, if the asymptotic bias from probit estimation of this equation is close enough to the one under Ordinary Least Squares, it can be shown that

$$(4.2.4) \quad p \lim \hat{\alpha} \simeq \alpha + \frac{Cov(\hat{u}, \varepsilon)}{Var(\hat{u})}$$

since the vectors  $\hat{u}$  and  $X$  are orthogonal to each other.

The term  $\frac{Cov(\hat{u}, \varepsilon)}{Var(\hat{u})}$ , is the OLS asymptotic bias which is equivalent to  $\frac{Cov(CH, \varepsilon)}{Var(\hat{u})}$  when the vector  $X$  is orthogonal to the column vector,  $\varepsilon$ . Therefore the asymptotic bias can be estimated practically by noting that

$$(4.2.5) \quad \begin{aligned} \frac{Cov(CH, \varepsilon)}{var(\hat{u})} &= \frac{Cov(CH, \varepsilon)}{Cov(X'\gamma, CH)} \frac{Var(X'\gamma)}{Var(\varepsilon)} \frac{Cov(CH, X'\gamma)}{Var(X'\gamma)} \frac{Var(\varepsilon)}{Var(\hat{u})} \\ &= \frac{Cov(CH, X'\gamma)}{Var(X'\gamma)} \frac{Var(\varepsilon)}{Var(\hat{u})} \end{aligned}$$

where the second equality follows the fact that the product of the first two terms on the right side of the equality is unit based on equation 4.2.2.

## 5 Empirical Results

### 5.1 Child labour and school attendance

I begin by discussing results from univariate probit regression that are presented in Table 4 under the constraint given by  $p = 0$ . Although these estimates may suffer from selection bias and do not take into account the joint determination of child labour and school attendance, they provide a useful benchmark for the results from my empirical model.

In the full sample as well as each of the two subsamples comprising of rural children and children from households with at least one adult occupied in a salaried job outside the household, univariate probit estimates show that child labour has a negative effect on the probability of school attendance. Across all samples, marginal effects from univariate probit models have the largest negative values. This implies that child labour has the greater negative effect on school attendance when it is treated as being determined independent of school attendance. The largest effect under univariate probit estimation occurs in the subsample for rural households. This suggests that child labour in rural areas has a higher adverse effect on school attendance when compared to its national average effect as estimated in the total effective sample. Because I don't study the channels through which child labour reduces school attendance and the fact that univariate probit estimates may be plagued by selection bias originating from unobserved variables, I do not interpret these results further. Nonetheless it is worth noting that the univariate probit model succeeds in producing a negative effect of child labour on school attendance as found by other empirical studies which I reviewed in the literature review section besides those from my empirical model presented below.

As additional useful reference point for my empirical estimates, I also report results from the unconstrained recursive bivariate probit model. As mentioned before, empirical

practitioners do not trust the estimates from this model in the absence of an exclusion restriction. Nonetheless it is a useful benchmark for my estimates of the correlation coefficient. The estimates of the correlation coefficient under this model are very close to negative one in all the three samples and significant tests show that they are statistically not equal to zero. This entails that the unconstrained model predicts that the amount of selection into child labour based on unobserved factors is quite huge. However this model shows that child labour has absolutely no effect on children school attendance because the value of its marginal effects are huge and fairly lower. Moreover the coefficients and marginal effects from this model carry a positive sign across all samples. The failure of this model to find any meaningful effect of child labour on school attendance can be attributed to endogeneity problem inherent in it. Since this model is estimated without any restriction that purges the effect of child labour, empirical researchers are highly skeptical about its results. Therefore I do not interpret its results any further. Instead I proceed to report results obtained from my empirical model which purges the unidirectional effect of child labour on children school attendance using condition 1.

Empirical results from my empirical model shows that child labour has a substantial negative effect on the probability of school attendance in all the three samples. The negative effect of child labour is highest and equal (-0.26) in the total households sample and the rural subsample. This equality in the marginal effects for rural and total children can be explained by the small difference between child labour in the total sample and the rural subsample given that eighty seven percent of children who participate in child labour reside in rural areas. When compared to the magnitude of the coefficients and marginal effects found from the univariate probit model, results in my empirical model are fairly lower. This implies that when child labour is treated as independently determined from school attendance, it leads to over estimation of the child labour effect which arises because selection on unobservables is completely ignored. Therefore once some combined effect of social networks, concern for children, society norms, religious beliefs and many other unobserved factors is taken into account, the estimated child labour effect declines. This result entails that unobserved variables affect school attendance positively and at the same time they affect child labour negatively. It also explains why the negative effect of child labour on school attendance declines once the strength of the negative relationship between unobserved variables begins to rise. This explains why the effect of child labour on school attendance is reversed despite being statistically zero in the unconstrained bivariate probit model.

But values of the correlation coefficients close to negative one cannot be trusted because they imply that conditional on observed variables, the role of unobserved variables is extremely large in the child labour and school attendance decision process. This is unlikely to be true because observed variables are carefully chosen so as to plausibly match the decision making process at household level. Similarly univariate probit esti-

mates produce large negative values because they assume that unobserved factors do not matter once observed factors have been known which is also unlikely to hold. Undoubtedly the role of unobserved factors in child labour school attendance decisions cannot be overlooked altogether. In order to avoid both extreme cases, this paper has taken a middle ground giving an equal weight to observed and unobserved factors in the decisions process which is captured by the assumption that the amount of selection from observed variables is equal to the amount of selection on unobserved variables (i.e.  $\rho_r = 0_s$ ).

Using the symmetry assumption, values of the correlation coefficients are found to be modest when compared to the ones obtained in the unconstrained bivariate probit model or the univariate probit model which implicitly assumes a correlation coefficient of zero. Surprisingly the values of the correlation coefficients in the total sample and the rural subsample which are -0.55 and -0.60 respectively, are quite close to -0.63 and -0.65 found by Nielsen (1998) respectively, even if the data are not directly comparable. These values of the correlation coefficients are undoubtedly not extreme. Because this paper does not study the specific channels through which child labour is transmitted into low school attendance, I cannot provide structural arguments which can be responsible for this result. Nonetheless I speculate based on Beegle et al. (2008) and Nielsen (1998), that the rate of return to child labour in rural areas might be an important conduit through which child labour causes low school attendance among children besides Bhalotra Heady's (2003) wealth paradox.

In sum, the results from this paper shows that child labour has a significant and substantial negative effect on the probability of school attendance among children. The largest negative effect of child labour on children school attendance is found among rural children. In households that have at least one adult member occupied in a salaried job, child labour is minimal and produces a less adverse effect on the probability of child labour. When compared to results obtained under two extreme cases namely, the bivariate probit without any constraint on the correlation coefficient and the univariate probit which assumes zero correlation, results in this paper are modest and superior.

Table 4: Empirical Estimates of Child Labour on Probability of School Attendance

Sample	All h/holds		Income h/holds		Rural h/holds	
	N = 6229		N = 3024		N = 2888	
Constraint	$\hat{\rho}$	$\hat{\alpha}$	$\hat{\rho}$	$\hat{\alpha}$	$\hat{\rho}$	$\hat{\alpha}$
$\rho = \frac{Cov(X'\beta, X'\gamma)}{Var(X'\gamma)}$	-0.55	-0.58 (0.16) [-0.26]	-0.67	-0.33 (0.19) [-0.17]	-0.60	-0.56 (0.18) [-0.26]
$\rho = 0$	0	-1.67 (0.19) [-0.50]	0	-1.90 (0.27) [-0.50]	0	-1.78 (0.23) [-0.54]
$\rho$ unconstrained	-0.89 (0.05)	0.30 (0.25) [0.16]	-0.97	0.56 (0.72) [0.23]	-0.90 (0.12)	0.26 (0.39) [0.17]

Note: clustered standard errors in parentheses. Marginal effects reported in brackets

## 5.2 Results on informal robustness of child labour effect to unobservables

In Table 5, I report estimates of the asymptotic bias and coefficient estimates of child labour that are used to compute the ratio which shows how much the normalized distribution of unobserved factors must shift when the normalized distribution of observables shifts in order to explain away the entire child labour effect. The values of the implied ratios for all the samples are reported in column 3. Going by the magnitudes of the implied ratios, a shift in the normalized distribution of unobservables that is more than two times greater than the one in the normalized distribution of observables, is required to explain the entire child labour effect. In the income households subsample a three times greater than shift in the distribution of unobservables is required. Because the implied ratios are greater than one, it is unlikely that such shifts will occur. Therefore I conclude that the negative effect of child labour on school attendance found in all the three samples is real.

Table 5: Informal Robustness of Child Labour Effect to Unobservables

$$\text{Model: } SCH = I(X'\gamma + \alpha CH + \varepsilon > 0)$$

$\alpha$  is estimated by probit regression

Sample	Asymptotic Bias	Estimate	Implied Ratio
	$\frac{Cov(CH,\varepsilon)}{Var(\hat{u})}$ (1)	$\hat{\alpha}$ (2)	$\hat{\alpha} / \frac{Cov(CH,\varepsilon)}{Var(\hat{u})}$ (3)
All Households N = 6229	-0.82 (0.16)	-1.67	2.04
Households with Income N = 3024	-0.60 (0.15)	-1.90	3.14
Households in Rural Areas N = 2888	-0.73 (0.11)	-1.78	2.44

Note: Analytic clustered standard errors reported in parentheses;

Due to perfect prediction of sector 3&10 dummies,  $\hat{\alpha}$  for rural sample is estimated with 2857 observations

## 6 Conclusion

Although the determinants of child labour and school attendance are well established in the literature, the causal effect of child labour on school attendance is largely unexplored owing in part to econometric challenges. The difficult in finding valid and strong instruments for child labour which is argued to be interdependent with school attendance is one such impediment. In this paper, I apply a novel estimation procedure to estimate the causal effect of child labour on children school attendance which does not require an instrument or exclusion restriction for child labour. Instead a point estimate of child labour is obtained under the assumption that the amount of selection bias from observed variables approximates the amount from unobserved variables. Since the variables introduced into the model are chosen to reduce bias, such an assumption is not very extreme. Empirical results suggest that child labour has a negative effect on the probability of school attendance once I control for the exogenous effects of demographic factors, household specific factors, income and regional location of the household. Informal methods of robustness checks indicate that the result is robust to selection on unobserved factors suggesting that the result is real. The largest negative effect of child labour on school attendance is found among children who live in rural areas while child labour has the

lowest effect among children who live with adults that are occupied in a salaried job. Results also show systematic differences between children who participate in child labour and their counterparts who do not. For example, children in child labour are relatively older, have less school participation rate, come from households whose heads spent relatively less time in school and are much older and eighty seven percent live in rural areas where they live as agriculture labourers. In terms of caveats, I caution against the misinterpretation of the results of this study since they are limited to a partial equilibrium setting that assumes the influence of all other factors are held constant. Lastly I propose that subsequent research should look into potential channels through which child labour is propagated into less school attendance.

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