YOUNG LIVES STUDENT PAPER

# The Impact of Child Labour on Educational Attainment: Evidence from Vietnam

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Paper submitted in part fulfilment of the requirements for the degree of Master of Science in Economics for Development at the University of Oxford, UK.

The data used come from Young Lives,, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (Andhra Pradesh), Peru and Vietnam over a 15-year period. **www.younglives.org.uk**

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Young Lives
An International Study of Childhood Poverty

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*The views expressed here are those of the author. They are not necessarily those of the Young Lives project, the University of Oxford, DFID or other funders.*

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*Abstract*

This study investigates the impact of child labour on educational attainment over a three-year horizon. Whilst this question has been explored by a plethora of studies in the literature, research focusing on the impact on school performance in developing economies is scarce. Employing a newly available dataset from the Young Lives survey and an instrumental variables strategy, this study examines the impact of working at age 12 on mathematics test scores three years later for children in Vietnam. In rural areas the evidence is suggestive that the impact of child labour is negligible. In urban areas, however, there is causal evidence that child labour significantly impedes educational attainment; a one standard deviation increase in hours worked reduces mathematics test scores by 12.45 points out of 100, or 67.85% of one standard deviation of the test score.

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# 1 Introduction

This study exploits a unique longitudinal data set from Vietnam to investigate the long-term impact of child labour on educational attainment. The findings show that working at the age of 12 has a significant adverse impact on educational attainment three years later in urban areas, but no effect in rural areas.

Child labour is a pervasive problem prevalent in the developing world. Notwithstanding international regulations restricting the type of permissible activities and participation age, progress towards its eradication has been slow. An estimated 215 million children aged 5-14 still participate in labour, just 3% lower than the 2004 level (ILO 2010).

The question addressed in this study is important for several reasons. Besides being undesirable on moral grounds, the general presumption is that child labour is harmful to children's educational development. Education is considered fundamental in empowering children to escape poverty, so labour is objectionable to the extent that it impedes a child's human capital development, perpetuating poverty into the future. Empirically however, it is ambiguous whether this widespread notion is validated, while some even argue that child labour may be beneficial by providing invaluable skills and informal education (Mortimer and Johnson 1997). The purpose of this study is to investigate which case is empirically true.

Vietnam provides an intriguing case study of the impact of child labour on educational attainment. Unlike most countries of the same level of economic development, the incidence of child labour in Vietnam is fortunately not as dramatic. Following the implementation of *Doi Moi* in 1986, a comprehensive programme of governmental socio-economic reforms, Vietnam has achieved remarkable progress, averaging growth rates of 7.5% between 1990-2004 (Duc et al. 2008). This has led to significant improvements. The poverty headcount ratio dropped from 75% in 1990 to 24.1% by 2004 (Government of the Socialist Republic of Viet Nam 2005), while the first Millenium Development Goal of eradicating extreme poverty and hunger has already been achieved.

Further, the incidence of child labour has declined significantly, falling from 45% to under 10% between 1993-2006, and is mostly observed in post-primary education ages only

(Rosati and Tzannatos 2006). Moreover, contrary to popular perceptions, most child labour does not take place in the formal labour market, nor is exploitative. Rather, most children participate in medium or low-intensity activities, including the family business or farm.

Concurrently, Vietnam is on track to achieving universal primary education. Access to education underwent a remarkable expansion between 1993-1998 (ILO 2010) with 97% of eligible children enrolled in primary education, while gender disparities are minimal. Vietnam has also adopted the Dakar Education for All Framework for Action, an initiative with a particular focus on improving education quality (Lan and Jones 2006).

Existing literature on the impact of child labour on educational attainment has several limitations, which this paper looks to overcome. Firstly, studies examining the impact on educational attainment in the form of test scores are rare. Most papers on developing countries investigate attendance or enrollment (Admassie and Bedi 2003, Ray and Lancaster 2005, etc.). However, there are many reasons why investigating test scores is to be preferred. Attendance is not an educational outcome but simply a time input into an educational production function. Since both attendance and labour are time allocation measures, a negative relation between them can arise due to the time constraint, regardless of the impact of child labour. Hence, attendance is agnostic to children's actual learning experiences; even if attending school, a child may still be adversely affected by working.

Considering enrollment poses further problems, as this does not even convey information on actual school attendance. To overcome these limitations, several studies (Psacharopoulos 1997, Phoumin 2008, Beegle et al. 2008, etc.) have looked at grade attainment relative to age; this too however is problematic. Different schools may have different regulations regarding grade completion or promotion, whilst the tests they administer, which determine whether a student repeats a year or gets promoted to the next, may also vary in difficulty (ILO 2010). Thus, measuring cognitive ability through performance is a better way to measure outcomes than enrollment or attendance. After all, the return to education is derived from what a child is actually able to do and not simply whether and for how many hours (s)he has attended school.

More importantly, the data employed in this paper makes test scores of particular interest. There is no significant variation in enrollment or attendance, with both being at very high levels, while most children are not behind in grade attainment relative to their age. These trends are characteristic of the high level of educational attainment in Vietnam, so investigating such measures would not be insightful. In fact, most children in the sample aspire to continue their studies to university level. Thus, investigating cognitive ability through test scores will be of much greater importance here, particularly because this outcome will determine whether and into which university they gain admission. Through the impact on future educational progress, test scores will have longer-term consequences and may significantly determine future wages. Even for those not progressing to university, cognitive skills may be more significant determinants of adult wages than years of schooling (Glewwe 1996).

In addition, the data allows for a different set of questions to be asked. Departing from other studies, which mostly focus on primary school age children, this paper looks at the impact of working at age 12 on test scores at age 15. This allows us to determine whether there is a negative impact of child labour at the secondary level, or if this effect may be age-dependent; for instance, older children may be more physically able to cope with work-related fatigue than younger children, so work may not be a significant disruption at higher ages. Moreover, work intensity in Vietnam is very low. This allows us to examine whether work still has adverse effects, regardless of its low duration.

Further, most studies treat child labour as exogenous and are thus unable to identify a causal impact on educational outcomes, but find a correlation at best. This study attempts to go beyond this by employing an instrumental variables strategy.

Lastly, the longitudinal nature of the data allows us to go beyond other studies that consider only the contemporaneous effect of child labour. To my knowledge, this is the first paper that investigates the *long-term* impact of child labour on educational attainment as measured by *test performance* in a developing country context.

The rest of this paper is organised as follows. Section 2 presents a review of the relevant literature. A data description is provided in Section 3. Section 4 explains the theoretical framework of the trade-off between child labour and educational attainment, while Section 5 identifies the empirical strategy. Section 6 presents the results, followed by robustness checks in section 7. Section 8 offers a discussion and section 9 concludes.

## 2 Literature Review

Recent years have seen a rapidly expanding literature on child labour[1]. Most studies examine its causes[2], while research focusing on the impact of child labour on educational attainment has predominantly considered school enrollment, attendance or grade attainment. Findings are mixed. Psacharopoulos (1997) found that working children in Venezuela and Bolivia were three times more likely to fail a year and had a two-year lower grade attainment relative to non-working children. Khanam and Ross (2008) also found a negative association between child labour and both school attendance and grade attainment for children aged 5-17 in rural Bangladesh. In contrast, Patrinos and Psacharopoulos (1997) failed to identify any impact of child labour on grade attainment in the case of Peru. Similarly, Admassie and Bedi's (2003) study found school attendance in Ethiopia to be affected only beyond 22 hours of child labour per week.

The aforementioned studies treated child labour as exogenous[3]; results from studies endogenising child labour are not however more conclusive. Ray and Lancaster (2005) found child labour to negatively affect school attendance following a multi-country study on Sri Lanka, Portugal, Belize, Cambodia, the Philippines, Namibia and Panama. Phoumin (2008) however, found grade attainment in Cambodia to be adversely affected only by work beyond 22 hours per week. In contrast, Beegle et al. (2008) found the impact on grade attainment in Tanzania to depend on gender; only males were significantly affected.

Literature investigating test scores in developing countries is scarce; most studies are restricted to developed economies such as the USA. Findings here are also mixed. Employing US data, Tyler (2003) found a significant negative impact of child labour on maths scores for 12th graders. Similarly, a negative impact on GPA scores was found by Stinebrickner and Stinebrickner (2003) in a study of college students of Berea college (Kentucky USA). In contrast, in a study of Washington high-school students, Schille et al. (1985) found part-time employment to increase the probability of achieving high GPA scores, with students working up to 20 hours a week achieving the highest score. Further,

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[1] For a review of the range of issues typically addressed, see Edmonds (2008).
[2] For a review of causes, see ILO (2004).
[3] Admassie and Bedi (2003) attempt to endogenise child labour as a robustness check, but acknowledge that their instruments are weak.

employing data on US high-school students, Lillydahl (1990), found that part-time work negatively affected on GPA scores but had no impact on SAT maths and vebal scores[4]. Amongst the rare studies that investigate the impact of child labour on test scores in developing countries, the findings are more homogeneous, although each suffers from significant limitations. Heady's (2003) study, based on the GLSS2 1988-89 data on primary school achievement in Ghana, found child work (excluding domestic chores) to adversely affect achievement as measured by test scores in reading and mathematics. The effect of domestic child work was found to be ambiguous. These results however cannot be given a causal interpretation as child labour was treated as exogenous.

A more comprehensive study is that of Gunnarsson et al. (2006), which investigated the impact of child labour on mathematics and language test scores using data on third and fourth year primary school students in nine Latin American countries[5]. Controlling for endogeneity, they found scores to be adversely affected; even children who worked 'only occasionally' attained on average 7.5% less in maths and 7% less in language tests than those not working. Nevertheless, this study also suffers from two significant limitations. Firstly, Latin American countries differ substantially by a multidimensionality of factors, including differences in school curricula. Estimating a pooled regression is therefore a questionable strategy, as it imposes a common education production function, ignoring significant cross-country heterogeneity. Secondly, their measure of child labour is vague; they classify it according to intensity by: almost never work, sometimes work, and often work. These categories lack sufficient information. For instance, a child working 'often' may be averaging 2-3 hours per day in Vietnam but 5-6 hours in Ethiopia.

Another related study is that of Bezerra et al. (2009), employing data from urban Brazil on school achievement tests in Portuguese and mathematics for 4th and 8th grade primary school students, and for 3rd year high-school students. Treating child labour as endogenous, they found that it adversely affected achievement, both across all three grades and across the two examined subjects. 4th graders who worked attained a mathematics score of nearly 10 points lower than those who did not; the equivalent impact was a reduction of 8 points in the 8th grade and 12 points in the 3rd year of high-school. Further, a one-hour increase in the amount of work was associated with a score reduction in the Portuguese exam of 3 points for 4th graders and 7 points for 12th graders. They also found that the effect varied by

[4] All of these studies on US data treated child labour as endogenous.
[5] These include Argentina, Bolivia, Brazil, Chile, Colombia, Dominican Republic, Honduras, Paraguay and Peru.

type of work; the effect was greater for work undertaken outside the household. The main limitation of this study is that it only investigates contemporaneous effects, offering no insights about the dynamic impact of child labour.

Research focusing on the consequences of child labour in Vietnam is rare. O'Donnell et al. (2005) considered health outcomes and found that child labour has no effect on child growth but increases the likelihood of future illnesses. A more comprehensive study is that of Beegle et al. (2009), which employed an instrumental variables strategy to evaluate the impact of child labour on health, education and wage work over a five-year period. They found that child labour had no impact on subsequent health but adversely affected school participation and educational attainment. Children working at the mean level of hours attained on average 1.6 years less education and had a 46% probability of dropping out five years later. However, they also identified an increased likelihood of subsequent wage work and thereby higher living standards for young adults who had worked as children.

# 3 Data Description

## 3.1 Overview

This study uses data on the old cohort of children from the 2$^{nd}$ and 3$^{rd}$ round of the Young Lives Longitudinal Survey in Vietnam. Young Lives is a long-term international research project tracking the livelihoods of 12,000 children over 15 years in four developing countries: Vietnam, Peru, Ethiopia and India (Andhra Pradesh). The Young Lives sampling approach is based on a sentinel site surveillance system, with the Vietnam sample divided into 20 clusters. Two groups within each country are followed: 2,000 children born in 2001-02 (the young cohort) and 1,000 children born in 1994-95 (the old cohort). The 1$^{st}$ round of data collection took place in 2002, followed by the 2$^{nd}$ round in 2006-07 and the 3$^{rd}$ in 2009. The attrition rate for Vietnam data is remarkably low (2.4%); round 2 contains data on 990 and round 3 on 976 of the initial 1,000 (old cohort) children interviewed.

The survey has the rare benefit of providing two measures of our key variable of interest; daily hours of child labour is reported by both the child and the caregiver, providing an opportunity to test for measurement error (discussed further in Section 7.2).

### 3.2 The Definition of Child Labour

The use of an appropriate definition of child labour is germane to extracting policy-relevant conclusions from any study of its consequences. The literature on child labour is highly inconsistent regarding this matter. This is not surprising, given the vague ILO definition of child labour as "work that deprives children of their childhood, their potential and their dignity, and that is harmful to physical and mental development" (ILO 2004, p.16). This poses the challenge of determining whether an activity is harmful to a child's development, especially because this largely depends on what alternative activities the child would be undertaking in the absence of work (Edmonds 2008).

In the data, daily hours of child labour are reported according to the following categories: paid work outside the household, unpaid work for the household (on family farm, cattle herding, shepherding or other family business), domestic chores (fetching water, firewood, cleaning, cooking, washing or shopping) and time spent caring for other household members (younger siblings, elderly or ill household members). Given the complexities imposed by ILO's nuanced definition, a compromised choice had to be made for practical reasons. The definition considered in this study is economic work, which is the sum of paid work outside the household and unpaid work for the household. To be consistent with the literature, it was also decided to use the measure reported by the caregiver, on the notion that child responses on retrospective data may be less reliable and more prone to measurement error.

### 3.3 Sample Restrictions

As the focus is to investigate to what extent child labour interferes with schooling, this study considers the 942 out of 976 children who were enrolled in school in round 2. Of these, only 428 have taken the maths test in round 3. Due to missing values on key variables of interest for 6 of these, the data employed in this study consists of 422 observations. Given the large loss of observations from the original sample, Section 7.1 investigates the possibility that these restrictions cause sample selection bias. Apart from the outcome variable of interest, maths scores in round 3, all other variables are taken from the base period, round 2.

**Table 1**. Summary Statistics

| Variable | **Full Sample** (422 obs) | | **Rural** (302 obs) | | **Urban** (120 obs) | |
|---|---|---|---|---|---|---|
| | Mean | s.d. | Mean | s.d. | Mean | s.d. |
| **Child characteristics** | | | | | | |
| Age | 14.754 | 0.442 | 14.715 | 0.459 | 14.850 | 0.381 |
| Male | 0.500 | 0.501 | 0.483 | 0.501 | 0.542 | 0.500 |
| Longterm Illness | 0.107 | 0.309 | 0.093 | 0.291 | 0.142 | 0.350 |
| BMI | 16.481 | 2.105 | 16.090 | 1.678 | 17.465 | 2.681 |
| **Caregiver Characteristics** | | | | | | |
| Ethnicity: Kinh | 0.950 | 0.2180 | 0.930 | 0.255 | 1.000 | 0.000 |
| Education: None | 0.038 | 0.191 | 0.036 | 0.188 | 0.042 | 0.201 |
| Education: Primary | 0.227 | 0.420 | 0.255 | 0.437 | 0.158 | 0.367 |
| Education: Lower Secondary | 0.514 | 0.500 | 0.540 | 0.499 | 0.450 | 0.500 |
| Education: Secondary/Higher | 0.220 | 0.415 | 0.169 | 0.375 | 0.350 | 0.479 |
| **Community Characteristics** | | | | | | |
| Community-level Rice Price | 5.148 | 0.506 | 5.150 | 0.573 | 5.140 | 0.269 |
| Rural | 0.716 | 0.452 | - | - | - | - |
| Region: Northern Uplands | 0.145 | 0.352 | 0.202 | 0.402 | 0.000 | 0.000 |
| Region: Red River Delta | 0.301 | 0.459 | 0.417 | 0.494 | 0.008 | 0.091 |
| Region: Mekong River Delta | 0.185 | 0.389 | 0.255 | 0.437 | 0.008 | 0.091 |
| Region: Central Coastal | 0.370 | 0.483 | 0.126 | 0.332 | 0.983 | 0.129 |
| **Household Characteristics** | | | | | | |
| Household Size | 4.761 | 1.362 | 4.732 | 1.326 | 4.833 | 1.451 |
| Has Access to Credit | 0.806 | 0.396 | 0.805 | 0.397 | 0.808 | 0.395 |
| Ln(consumption/capita) | 4.730 | 0.466 | 4.640 | 0.411 | 4.956 | 0.517 |
| Ln(Assets value/capita) (/1000) | 3.901 | 5.338 | 3.783 | 4.703 | 4.200 | 6.686 |
| Land Area Owned ($m^2$) (/1000) | 3.578 | 7.008 | 4.914 | 7.885 | 0.216 | 0.745 |
| **Education Measures** | | | | | | |
| Enrolled in school (both rounds) | 1.000 | 0.000 | 1.000 | 0.000 | 1.000 | 0.000 |
| Attends Public School | 1.000 | 0.000 | 1.000 | 0.000 | 1.000 | 0.000 |
| Attends Extra Maths Classes | 0.656 | 0.475 | 0.589 | 0.493 | 0.825 | 0.382 |
| Hours/week Extra Maths Class | 2.205 | 2.463 | 1.820 | 2.455 | 3.175 | 2.213 |
| PPVT score (round 2) | 143.371 | 19.035 | 140.683 | 21.058 | 150.034 | 10.028 |
| Maths test score (round 2) | 7.808 | 1.466 | 7.702 | 1.504 | 8.076 | 1.334 |
| Maths test score (round 3) | 53.733 | 23.312 | 50.766 | 24.411 | 61.200 | 18.349 |
| **Child Labour Measures (hours per day, reported by caregiver)** | | | | | | |
| Any activity (Total) | 1.877 | 1.481 | 2.215 | 1.462 | 1.025 | 1.156 |
| Economic Work (Total) | 0.505 | 1.038 | 0.679 | 1.155 | 0.067 | 0.404 |
| Economic Work: for Pay | 0.019 | 0.228 | 0.017 | 0.207 | 0.025 | 0.274 |
| Economic Work: not for Pay | 0.486 | 1.022 | 0.662 | 1.146 | 0.042 | 0.301 |
| Domestic Work (Total) | 1.372 | 1.158 | 1.536 | 1.151 | 0.958 | 1.072 |
| Domestic Work: Chores | 1.083 | 0.855 | 1.225 | 0.852 | 0.725 | 0.756 |
| **Child Labour Measures (hours per day, reported by child)** | | | | | | |
| Economic Work (Total) | 0.590 | 1.137 | 0.778 | 1.271 | 0.071 | 0.414 |

### 3.4 Salient Features

Table 1 summarises the key variables of interest for three samples: all 422 children, the 302 (72%) that reside in rural areas and the 120 (28%) that reside in urban areas. All children are of the same approximate age (14.75) while the gender distribution is balanced. About 10% of the full sample is suffering from long-term illnesses. The average BMI is 16.48 (the range 15-21 is considered healthy). Long-term illnesses are slightly more prevalent in urban areas, where average BMI is nevertheless higher.

The second section presents statistics on family background by considering the child's primary caregiver. 95% are ethnically Kinh. Approximately 50% have lower secondary education, while the proportion with no education is very low in both rural and urban areas (under 5%). More than twice as many caregivers have secondary/higher education in urban areas than in rural areas.

The next section describes community characteristics. The households come from four regions: Northern Uplands (14.5%), Red River Delta (30.1%), Mekong River Delta (18.5%) and Central Coastal (37%). Average community-level rice prices, measured per kilo, are 5.15VND (Vietnamese Dong). Prices are almost identical across rural and urban areas, although the standard deviation in rural areas is twice as large as the one in urban areas. Rice prices will be used as an instrument for child labour (discussed in section 7.4).

Next, household characteristics are presented. The average size is approximately 4.76 members per household, while 80% of households have access to credit. Two indicators for the standard of living are considered: the log of per capita consumption[6] and the log of the value of assets per capita[7], both measured in VND. Urban households fare better across both. Rural households however own much more land (measured in square metres[8]), indicative of the agricultural nature of rural household production.

[6] This is the sum of consumption of food purchased from the market, food produced from the household's harvest/livestock and food received as gifts, in the two weeks preceding the survey. Consumption was chosen over income/expenditure measures for several reasons. Besides being easier to measure, especially in rural areas where most households are self-employed and mainly consume home-produced goods, consumption is a better indicator of wellbeing due to Engel effects; most spending of poor households is on food.

[7] Assets include the value of livestock, physical assets and cash holdings. Note that this variable has been scaled down by a factor of 1000 to facilitate interpretation, as the low value of the VND currency makes the asset values disproportionally large.

[8] As with assets, this has also been scaled down by a factor of 1000 to facilitate interpretation.

Educational measures are then summarised. All children are enrolled in school in both the 2nd and 3rd round of the Young Lives survey, and all attend public schools. Extra maths tuition is prevalent; the attendance rate is 65.6% in the full sample, 58.9% in rural and 82.5% in urban areas. Intensity is also higher in urban areas; average hours of weekly attendance of extra classes for mathematics is 3.18, compared to 1.82 in rural areas. In terms of educational outcomes, two tests were administered in round 2: the Peabody Picture Vocabulary Test (PPVT) and a maths test. The PPVT is a test of cognitive ability and can take any value from 0 to 204, while the maths test takes values from 0 to 9. A different maths test was administered in round 3, taking values from 0 to 100. This is the main outcome variable in this study, while the two former tests will be used for robustness checks (discussed in sections 6 and 7). Children scored on average 143.37 in the PPVT, 7.81 in the round 2 maths test and 53.73% in the round 3 maths test. Urban children performed better on all tests, while the distribution of their scores is also lower.

Further, table 1 summarises the intensity of child labour as reported by caregivers. The average daily hours of work on any activity are 1.88. The intensity of economic work is low (0.505 hours), with most of this (0.486) being spent on non-wage work for the household. The proportion of hours of economic work spent on wage labour is much higher in urban areas (37.31%) than in rural areas (2.5%). The intensity of domestic work (1.37 hours) is much higher than economic work, with most time devoted to domestic chores (1.08 hours). Children work longer in rural than in urban areas across all activities except economic work for pay. Lastly, statistics of economic work reported by the child are shown. While very similar to the caregiver reported measures, they have a marginally higher mean and standard deviation. This variable will be used to instrument for measurement error in Section 7.2.

# 4 Theoretical Framework

## 4.1 The Decision Between Child Labour and Schooling

The level of child schooling and labour is determined by parents' decisions, which in turn depend upon the costs and benefits of the available education and work opportunities. Educating a child involves costs, both direct (school fees, extra tuition, school uniforms) and indirect (travel time, time spent at school, extra classes and home study). This time input for schooling could be used for work and so the opportunity cost of educating a child is the forgone income that the household would otherwise raise. Education also has substantial benefits; it allows a child to accumulate human capital and earn higher future earnings. Hence, the impediment of human capital development is the main cost of child labour. The magnitude of this cost depends on many factors, including school quality and wage-work opportunities; low quality schooling or lack of high-paying jobs will decrease the return to formal education. Further, the benefits of child labour may also be substantial. Not only does it contribute to the household directly through income raised by the child, but it may also free a parent from some family-related activities and allow him to search for wage labour outside the household business or farm. A simplified model exemplifying the basic trade-off between child labour and schooling is the following:

A child lives for two periods $(t=1,2)$. In the first period the child spends $E_1$ hours attending school and other education-related activities and may or may not work for $L_1$ hours. The time constraint is $E_1 + L_1 = 1$ (for simplification, we abstract here from time for leisure and sleep). In period 2, the child becomes an adult and just works: $L_2 = 1$. Income[9] $W(H_t)$ generated by working in period $t$ depends on the child's level of human capital accumulation up to that point, $H_t$.

In period 1, the child's human capital is at an initial endowment level, $H_1$, and the child has the option of attending school. In period 2, the child's human capital is a function of the level of human capital at the start of the previous period and the amount of schooling received during that period: $H_2 = H(H_1, E_1)$. For ease of exposition, assume this takes a Cobb-Douglas form: $H_2 = (H_1^{\alpha} E_1^{1-\alpha})$. From the time constraint, $E_1 = 1 - L_1$. Substituting this into $H_2$ gives us $H_2 = H_1^{\alpha}(1-L_1)^{1-\alpha}$. Hence, $H_2$ is increasing in $H_1$ and decreasing in $L_1$, hours worked. Thus, a child is sent to work for $L_1$ hours in period 1 iff:

$$L_1 W(H_1) + \frac{W\left[H_1^{\alpha}(1-L_1)^{1-\alpha}\right]}{1+r} \geq \frac{W\left(H_1^{\alpha}\right)}{1+r} \tag{1}$$

which implies:

$$L_1 W(H_1) \geq \frac{W\left(H_1^{\alpha}\right)\left[1-(1-L_1)^{1-\alpha}\right]}{1+r} \tag{2}$$

[9] Since the focus here is on the hours of child labour, we assume for simplification that the returns from working are the same, whether the parents choose to send their child to work in the market or on household activities such as farming.

Hence, a child will work for $L_1$ hours if the current benefits to the family, through higher family income, outweigh the future benefits to the child, through higher human capital.

## 4.2 The Impact of Child Labour on Educational Attainment: Theory

Child labour is widely perceived to impede the educational attainment of children in a multitude of ways. Fundamentally, since both are time inputs, work competes with time devoted to education related activities such as attending school, attending extra classes and completing homework. Left with less time for school and study, working children are not able to derive the same educational benefit as their non-working counterparts. Child labour may also be strenuous, causing exhaustion and leaving children lacking energy, impeding their ability to focus in the classroom or on home study. Even if they devote the same amount of hours to attendance and study as children who don't work, their lack of energy could hamper their ability to gain the same returns from the learning process.

Nevertheless, child labour may have no effect on educational attainment. If children work as opposed to doing nothing, this will not jeopardise time that would otherwise be used as an input to educational activities. Even if it does, the impact of child labour may be insignificant if the intensity of working is very low, if their activities are not particularly straining, or if working helps children become more efficient in their time use.

Further, child labour may even be beneficial to educational attainment. Working allows children to put to practice skills learnt at school, thereby solidifying their knowledge. For instance, working for the family business may facilitate the development of their quantitative competence, acting as informal 'extra tuition' where the child is required to apply his/her numeracy skills to real world situations. Juggling between working and school may also enhance children's time management skills, making them more efficient in studying. Moreover, working can provide children with a sense of self-esteem, responsibility and confidence. For instance, a study of children's contributions to the household economy in Ethiopia found that working is a source of pride for the children themselves (Heissler and Porter 2010). Working may therefore develop children's human and psychosocial capital that may improve their performance in school.

# 5 Empirical Framework

## 5.1 The Empirical Strategy

The investigation of the question posed by this study requires the estimation of an education production function. Just as any test of the relation between child labour and educational attainment, a number of confounding factors must be taken into account. Firstly, it should control for child-specific characteristics such as age; we expect older children to perform better, for example due to being in school longer. It should also account for gender differences; boys are likely to work more while girls are likely to devote more time to household chores. Health should also be considered; ill children are likely to work less but also perform worse. Importantly, it should also account for innate ability, as this will be a significant determinant of both the parents' choice of how much a child should work, and the child's educational attainment. Although this is infeasible, as ability is unobserved, it is imperative that the production function considers background characteristics, such as the caregiver's educational level, to at least capture inherited ability. Household characteristics such as wealth and size should also be accounted for, as these determine how much households spend on schooling, which in turn affects school performance. Further, school-input controls should be incorporated. While no objective school-quality measure exists in the data, village fixed effects could implicitly capture the effects of different schools by location[10]. Time spent on extra tuition should also be accounted for. Not only does it directly affect educational attainment, but it also captures parental investment choices and aspirations for their children's education.

To take these considerations into account, this study investigates the impact of child labour on educational attainment over a three-year horizon using the following OLS specification:

$$y_{it+3} = \alpha + \beta l_{it} + x'_{1it}\gamma_1 + x'_{2it}\gamma_2 + x'_{3it}\gamma_3 + x'_{4it}\gamma_4 + x'_{5it}\gamma_5 + \varepsilon_{it+3} \quad (3)$$

Period *t* refers to the round 2 survey and period *t+3* to round 3. In line with the language used in the program evaluation literature, the treatment here is defined as the hours per day, $l_{it}$, that a child participates in economic work in round 2. The outcome $y_{it+3}$ is the round 3

[10] Including these renders regional controls unnecessary, as village fixed effects are more informative.

maths test score, measured three years after the treatment[11]. Each of the $x'_{jit}$ vectors includes controls, measured for child *i* at time *t*, to account for the aforementioned factors that the education production function should include. They facilitate the identification of the impact of child labour by controlling for observable characteristics that may affect school and work outcomes and that may otherwise cause omitted variable bias. $x'_{1it}$ includes child characteristics: age, gender and health. $x'_{2it}$ accounts for caregiver characteristics: education and ethnicity. $x'_{3it}$ controls for household characteristics: rural/urban location, log consumption per capita, log asset value per capita, credit access and household size. $x'_{4it}$ controls for the weekly hours of extra maths classes, and $x'_{5it}$ includes village fixed effects.

A First-Differences model could also be plausibly employed. It would allow us to exploit the panel nature of the data further; importantly, it would eliminate an important source of bias: time-invariant unobserved ability. However, this approach was rejected for many reasons. First, it would be answering a different question. Secondly, it would be assuming that score improvement is possible, which may not hold for students in the top decile. This could lead to inferences that child labour is impeding the progress of such students when the true cause may be their initial high achievement. Further, it relies on the tenuous assumption that the impact of child labour is the same at all ages, even though we may expect older students to be more able to cope with work. Most importantly, working at age 15 is not considered as child labour in Vietnam, so treating it as such would be misleading.

The OLS specification was therefore preferred. The restrictions imposed on the sample avoid some identification complications that would prevail had we also considered children who were not enrolled in school in round 2; the effect of child labour would be confounded by the effect of not attending school. Solving this would require the addition of a school attendance variable, creating additional problems of identification, by having to identify separate effects of child labour and schooling in round 2 on educational attainment in round 3 (Beegle et al. 2009). Further, the fact that the children considered were all enrolled in round 3 also facilitates the identification process; we would otherwise have to identify separate effects for both those enrolled and those not enrolled when the test was taken.

[11]No child has attained a maths score of zero, so potential censoring of the outcome variable at zero is not an issue in this study.

The coefficient of interest of this study is $\beta$. The main hypothesis to be tested is whether the general notion that child labour has a negative impact on educational attainment is empirically true, i.e. whether $\beta < 0$.

### 5.2 Potential Problems

There a number of potential problems associated with estimating the OLS specification. These include whether results are sensitive to the choice of using economic work as the definition of child labour, selection bias, measurement error, omitted variable bias on both time variant and time invariant unobservables, endogeneity of child labour, wrong functional form, and heteroscedasticity and non-normality of the residuals. Apart from the last two issues, all other problems violate the critical OLS zero-conditional mean assumption. Each is addressed below.

The implications of defining child labour as economic work deserve some attention, as there are two caveats associated with ignoring domestic chores. Firstly, the distinction between unpaid work for the household and domestic chores may be opaque, particularly in rural settings[12], so economic work alone may not capture the full impact of activities undertaken by working children. Secondly, girls are more likely to engage in domestic chores, so focusing exclusively on economic work may understate the impact of female participation in domestic chores on their educational attainment.

Another problem may be sample selection bias. Only 422 out of a total of 976 children took the test, so this study can only investigate the impact of child labour on educational attainment of this specific sub-group, not the full sample. If the choice to take the test was not random but related to the outcome of interest, the OLS results will be prone to selection bias. This will be the case if the likelihood of taking the test is related to the children's performance expectations. In such a case, OLS results will be biased, underestimating the true impact of child labour.

However, even if sample selection is not a problem, two other potential sources of selection bias still exist: within-household and between-household selection. Within-household selection arises because parents may decide whether and for how long their child should

[12] Consider the example of a child fetching water for the father who is working on the family farm. If the water is intended for the father's personal use, it would be categorised as a domestic chore. If the father requested water to give to an animal, it would be categorised as unpaid work for the household, although the same time and effort is required of the child in both cases.

work based on unobservable child characteristics such as innate ability. This implies that, while specification (3) is the equation we estimate, the true model is:

$$y_{it+3} = \alpha + \psi_i + \beta l_{it} + x'_{1it}\gamma_1 + x'_{2it}\gamma_2 + x'_{3it}\gamma_3 + x'_{4it}\gamma_4 + x'_{5it}\gamma_5 + \varepsilon_{it+3} \quad (4)$$

where $\psi_i$ is the time-invariant, unobserved ability of child *i*. Unequivocally, test scores are partly determined by each child's inherent ability. The bias arises if this ability affects the parents' decision on how long their child should work, i.e. if $l_{it} = \delta\psi_i$ implying:

$$\hat{\delta} = \mathrm{cov}(\psi_i, l_{it}) / \mathrm{var}(l_{it}) \quad (5)$$

It can be shown that the resulting bias is:

$$p\lim \tilde{\beta} = \beta + \mathrm{cov}(\psi_i, l_{it}) / \mathrm{var}(l_{it}) \quad (6)$$

Depending on the sign of the covariance, the bias can be positive or negative, so the net effect on the estimate of the impact of child labour is ambiguous. For example, parents may decide that a child of low ability should work more, since the return from schooling is likely to be low regardless of working. On the other hand, parents may believe that, given this low return, less able children should work less in order to focus on school and gain as much as possible out of education, since these children will be most vulnerable to the effect of child labour and less able to combine work and school. Hence, as long as hours of work are correlated with the child's innate ability, OLS results will be biased.

Unobserved ability bias can be a problem even in the absence of within-household selection, since it is considered to be an important determinant of educational outcomes in the human capital literature. However, this problem may not be as severe as is theoretically perceived to be. In a similar study on Ghana, Heady (2003) found that controlling for ability via a Ravens test did not affect his results, while Card (1999), shows that the ability bias in studies estimating the returns to schooling appears to be small. Moreover, it is questionable whether ability is truly innate and not time-variant.

Further, between-household selection is also a concern, since household heterogeneity may also partly determine which households choose to send their children to work and for how long. In poor households, child labour may provide a way of supplementing the insufficient resources of the family. This is central in Basu and Van's (1998) model – child labour is only observed when a family cannot otherwise meet its subsistence requirements. Similarly, in cases where the schooling quality available to households is very poor, parents may encourage child labour, seeing this as the only means to provide some opportunities for children to develop their skills and enhance their future employment prospects. Moreover, child labour may also be used as a risk-coping mechanism, especially in rural households and in settings of imperfect insurance or credit markets. In our model, certain wealth measures are included as covariates, but no objective data exists on school quality. Moreover, these do not address other potential sources of between-household selection such as cultural reasons affecting child labour supply or parents' ambitions for the child's future. While the former may partly be captured by controlling for caregiver ethnicity, and the latter by accounting for hours of extra classes parents choose to send their children for, it is possible that other unobserved factors have not been accounted for.

A further source of bias is measurement error in the hours worked variable. This is a measure of the time spent on a given activity in a typical day. Responses are based on approximations of recollections concerning retrospective time usage, as it is unreasonable to expect that respondents have kept written records of such data. As such, they are prone to measurement error. Unless resolved, OLS results will have attenuation bias, underestimating the true impact of child labour.

Moreover, the specification imposes a constant marginal effect of child labour. If the true impact is, however, non-linear, results will be biased due to wrong functional form. Finally, OLS statistical inference requires the residuals of the estimated equation to be independently and identically distributed. Since data was collected at cluster level, the residuals are likely to be correlated within clusters, rendering statistical inference incorrect if not accounted for. Possible non-normality of the residuals will also hamper inferences.

Overall, OLS results are likely to be biased and inconsistent due to omission of unobservable characteristics and measurement error. They can at best indicate an association between the treatment and outcome, but do not allow for causal inferences.

### 5.3 Potential Solutions and Robustness Checks

Various methods are employed to resolve these issues. The most serious source of bias is unobserved ability, so one attempt to address this is by incorporating an observed proxy:

PPVT scores. This is a type of intelligence test assessing individual verbal and scholastic abilities. As such, it does not test school related material and can be considered an, albeit imperfect, proxy for innate ability. Of course, it does not capture all aspects of ability, one of which is inherited ability, which is nevertheless accounted for by variables of the caregiver's background. While incorporating PPVT scores and caregiver background is not enough to fully control for innate ability, this is the best that can be done given the available data. The OLS specification therefore includes caregiver characteristics and also tests whether controlling for a proxy of ability changes the results.

To account for the opacity of the definition of child labour, household chores are also included to test whether results are sensitive to excluding them. An interaction term between chores and gender is also used to test if this effect is gender specific.

Adding controls to the main specification addresses the two aforementioned problems. Further robustness checks follow. First, the specification is tested for sample selection. Then, the hours worked variable is tested for measurement error by using hours reported by the child as an instrument. Functional form tests then follow to investigate whether the impact of child labour is non-linear. Lastly, instrumental variables are used to address any remaining sources of bias arising from the endogeneity of the hours worked variable.

In addition, standard errors are adjusted by clustering at the community level. Further, the residuals of all regressions were tested for non-normality by Shapiro-Wilk and Skewness-Kurtosis tests. The null hypothesis of normality could not be rejected at the 10% level for any regression. Thus, the statistical inferences that follow are robust to these problems.

## 6 OLS Results

Table 2 presents the OLS results for the pooled sample. As column (1) indicates, there is evidence of a negative association between hours worked and maths scores. Unconditional on hours worked, a one s.d. increase in hours worked reduces maths scores by 4.86 points (out of 100). However, introducing controls for socio-economic characteristics and village fixed effects (column 2) greatly reduces this effect to just 0.17 points and renders hours worked statistically insignificant at the 10% level. Hours worked remain insignificant after further controlling for ability through PPVT scores (column 3). The main determinants of maths scores appear to be the child's health (whether it is suffering from a long-term illness and its BMI), the caregiver's ethnicity, hours of extra maths classes attended, whether the household is rural and village fixed effects. Strikingly, children in rural areas score on average 13.64 points less than their urban counterparts.

Due to this large disadvantage of children in rural areas, and given the large heterogeneity between types of work undertaken in rural and urban households, column 4 introduces an interaction term between hours worked and a rural dummy variable to investigate this further. Now, both hours worked and the interaction term are statistically significant at the 1% level. The negative effect of child labour is driven by the urban observations. The impact on scores is larger than before for urban children, but negligible for rural children: a one s.d. increase in hours worked is associated with a reduction in scores of 7.95 points (out of 100) in urban areas but of only 0.30 points in rural areas. Controlling for ability (column 5) does not change the statistical significance of the results, but exacerbates the difference in the impact of hours worked on scores between urban and rural children (the score reduction becomes 10.21 points for urban and 0.06 points for rural children).

To further investigate these large disparities, the model was then estimated separately for rural and urban children. Table 3 presents the results, confirming that the negative impact of child labour is driven by the urban observations; in fact, in rural areas working seems to be positively associated with test scores (column 1). This effect however is not significantly different from zero. The determinants of test scores in rural areas are, as before, health, caregiver's ethnicity and village fixed effects, but extra maths tuition ceases to matter. Controlling for ability (column 2) has no effect besides making long-term illness insignificant. A variable for household chores, and its interaction with a gender dummy (taking the value of 1 for males), were then introduced (columns 3-6) to test if previous results are sensitive to not considering chores as labour. Both terms are statistically insignificant (columns 3 and 5). This is robust to controlling for ability (columns 4 and 6). Although statistically insignificant, the positive interaction term confirms our expectation of a larger impact of chores on females (for each hour of chores, males score higher).

The urban sub-sample confirms the negative association between hours worked and test scores found in the pooled regression, although the impact is now smaller; as column 7 shows, a one s.d. increase in hours worked is associated with a score of 2.60 points lower (compared to 7.95 lower). Controlling for ability (column 8) increases this adverse impact to a 3.59 points reduction. This result is statistically significant at the 5% level. In contrast to the rural sample, the only other significant determinants of maths scores are extra tuition and village fixed effects. Similar to the rural sample however, household chores and its interaction with gender (columns 9-12) are not statistically significant.

**Table 2**. Dependent Variable: Round 3 Maths Scores

| | **Pooled Sample** | | | | |
|---|---|---|---|---|---|
| Variables | (1) | (2) Village FE | (3) Village FE | (4) Village FE | (5) Village FE |
| Hours of economic work (per day) | -4.678** (1.836) | -0.161 (1.189) | -0.534 (1.430) | -7.663*** (1.750) | -9.835*** (2.800) |
| Hours of economic work X Rural | | | | 7.954*** (1.967) | 9.888*** (2.902) |
| Age | | 1.829 (3.128) | 2.129 (3.038) | 1.527 (3.214) | 1.724 (3.140) |
| Male | | -2.576 (1.657) | -2.552 (1.612) | -2.631 (1.622) | -2.661 (1.594) |
| Longterm illness | | -9.643** (3.757) | -9.254** (4.221) | -9.593** (3.782) | -9.166** (4.238) |
| BMI | | 1.074*** (0.375) | 1.047** (0.374) | 1.090*** (0.374) | 1.074*** (0.374) |
| Rural | | -19.701*** (6.458) | -13.638*** (2.615) | -19.952** (7.118) | -13.009*** (2.731) |
| Household Size | | 0.383 (0.824) | 0.426 (0.789) | 0.312 (0.837) | 0.339 (0.802) |
| Credit Access | | 0.116 (2.426) | 0.308 (2.612) | -0.695 (2.688) | -0.599 (2.757) |
| Ln(Consumption/capita) | | -2.441 (2.836) | -1.990 (2.476) | -2.414 (2.805) | -1.950 (2.443) |
| Ln(Assets/capita) | | -0.228 (0.159) | -0.216 (0.161) | -0.226 (0.157) | -0.212 (0.160) |
| Caregiver Ethnicity: Kinh | | -8.766** (3.395) | -7.870** (3.239) | -8.508** (3.416) | -7.518** (3.327) |
| Caregiver Education: primary | | -0.244 (5.751) | 3.641 (6.451) | 0.704 (5.829) | 4.817 (6.490) |
| Caregiver Education: intermediate | | -2.712 (4.151) | 0.373 (4.762) | -2.410 (4.210) | 0.635 (4.786) |
| Caregiver Education: secondary/higher | | 0.643 (4.643) | 3.866 (5.822) | 1.113 (4.656) | 4.288 (5.784) |
| Maths Extra Classes (hours/week) | | 1.003** (0.416) | 0.944** (0.443) | 1.009** (0.418) | 0.952** (0.445) |
| PPVT Score | | | 0.046 (0.087) | | 0.040 (0.083) |
| Constant | 56.094*** (2.790) | 22.825 (53.581) | 73.754 (55.723) | 28.453 (54.992) | 78.357 (57.143) |
| Joint F-test on village fixed effects (F-stat) | | 3917.59 | 1477.81 | 4336.02 | 3148.87 |
| Observations | 422 | 422 | 422 | 422 | 422 |
| $R^2$ | 0.0434 | 0.3676 | 0.3643 | 0.3722 | 0.3716 |

Cluster-robust standard errors in parentheses; * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

**Table 3.** Dependent Variable: Maths Scores round 3

| | Rural | | | | | | Urban | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | (1) Village FE | (2) Village FE | (3) Village FE | (4) Village FE | (5) Village FE | (6) Village FE | (7) Village FE | (8) Village FE | (9) Village FE | (10) Village FE | (11) Village FE | (12) Village FE |
| Hours of Economic | 0.387 | 0.192 | 0.555 | 0.349 | 0.568 | 0.355 | -6.430* | -8.892** | -6.432* | -8.864** | -6.262* | -8.631** |
| Work (per day) | (1.151) | (1.333) | (1.171) | (1.357) | (1.188) | (1.370) | (2.616) | (2.607) | (2.903) | (2.708) | (2.679) | (2.532) |
| Hours of Household | | | 1.905 | 1.838 | 1.557 | 1.591 | | | 3.906 | 3.893 | 2.922 | 1.858 |
| Chores (per day) | | | (1.445) | (1.576) | (2.199) | (2.369) | | | (2.429) | (3.159) | (1.433) | (1.638) |
| Hours of Household | | | | | 0.800 | 0.579 | | | | | 2.367 | 4.652 |
| Chores X Male | | | | | (3.840) | (4.094) | | | | | (3.263) | (3.873) |
| Age | 1.748 | 2.452 | 1.517 | 2.256 | 1.488 | 2.239 | 0.235 | -1.257 | 0.588 | -0.758 | 0.548 | -0.916 |
| | (4.237) | (4.052) | (4.213) | (4.068) | (4.219) | (4.077) | (3.874) | (3.096) | (4.351) | (3.760) | (4.435) | (3.801) |
| Male | -2.924 | -2.457 | -2.202 | -1.796 | -3.153 | -2.487 | -3.216 | -3.855 | -0.882 | -1.441 | -2.491 | -4.701 |
| | (2.376) | (2.339) | (1.932) | (1.878) | (4.615) | (4.745) | (3.275) | (3.432) | (1.322) | (1.394) | (3.451) | (4.026) |
| Long-term Illness | -11.615** | -10.865 | -11.451 | -10.633 | -11.419* | -10.598 | -5.906 | -7.366 | -5.890 | -6.933 | -5.543 | -6.419 |
| | (5.447) | (6.337) | (5.501) | (6.449) | (5.544) | (6.546) | (4.390) | (5.126) | (4.464) | (4.884) | (4.585) | (4.738) |
| BMI | 1.640*** | 1.510*** | 1.553*** | 1.440** | 1.549*** | 1.437** | 0.294 | 0.304 | 0.247 | 0.261 | 0.294 | 0.355 |
| | (0.453) | (0.495) | (0.486) | (0.535) | (0.482) | (0.536) | (0.389) | (0.509) | (0.416) | (0.522) | (0.451) | (0.590) |
| Household Size | -0.187 | -0.075 | 0.037 | 0.151 | 0.027 | 0.146 | 1.291 | 1.306 | 1.288 | 1.383 | 1.262 | 1.314 |
| | (1.095) | (1.054) | (1.163) | (1.121) | (1.178) | (1.133) | (1.212) | (1.393) | (1.360) | (1.546) | (1.342) | (1.468) |
| Credit Access | -2.200 | -2.242 | -1.908 | -1.914 | -1.934 | -1.930 | 3.701 | 4.346 | 3.955 | 5.067 | 3.790 | 4.595 |
| | (3.476) | (3.796) | (3.300) | (3.642) | (3.326) | (3.645) | (4.658) | (3.949) | (4.121) | (3.532) | (4.520) | (3.946) |
| Ln(Consumption/ | -2.075 | -1.247 | -1.762 | -0.952 | -1.757 | -0.953 | -3.025 | -0.992 | -2.246 | -0.336 | -2.304 | -0.398 |
| capita) | (3.781) | (3.354) | (3.924) | (3.519) | (3.919) | (3.517) | (3.928) | (2.043) | (3.697) | (2.014) | (3.747) | (2.111) |
| Ln(Assets/capita) | -0.212 | -0.192 | -0.183 | -0.166 | -0.179 | -0.164 | -0.164 | -0.179 | -0.118 | -0.135 | -0.118 | -0.137 |
| | (0.318) | (0.331) | (0.300) | (0.313) | (0.307) | (0.321) | (0.129) | (0.132) | (0.107) | (0.112) | (0.115) | (0.124) |
| Caregiver Ethnicity: | -8.094** | -7.861** | -9.167** | -8.897** | -9.041** | -8.798** | | | | | | |
| Kinh | (3.617) | (3.662) | (4.080) | (4.083) | (4.034) | (4.055) | | | | | | |
| Caregiver Education: | 0.102 | 5.680 | 0.585 | 6.117 | 0.461 | 6.011 | 3.755 | 8.262 | 5.036 | 8.645 | 4.463 | 7.877 |
| Primary | (8.565) | (10.265) | (8.891) | (10.456) | (9.075) | (10.692) | (9.075) | (7.696) | (9.450) | (8.599) | (8.913) | (8.034) |
| Caregiver Education: | -3.926 | 1.344 | -3.334 | 1.902 | -3.554 | 1.724 | 0.773 | 2.984 | 1.169 | 2.684 | 0.527 | 1.681 |
| Intermediate | (6.352) | (7.801) | (6.672) | (7.903) | (6.886) | (8.242) | (3.849) | (4.670) | (3.693) | (4.822) | (3.234) | (4.312) |
| Caregiver Education: | 1.801 | 7.177 | 2.172 | 7.540 | 1.811 | 7.272 | 0.671 | 3.463 | 0.993 | 2.978 | 0.361 | 2.028 |
| Secondary/Higher | (7.340) | (9.494) | (7.658) | (9.613) | (8.378) | (10.401) | (3.796) | (4.814) | (3.929) | (5.224) | (4.773) | (5.661) |
| Maths Extra Classes | 0.833 | 0.716 | 0.846 | 0.737 | 0.835 | 0.729 | 1.532 | 1.739* | 1.477 | 1.698 | 1.478 | 1.689 |
| (hours/week) | (0.583) | (0.621) | (0.580) | (0.626) | (0.604) | (0.656) | (0.965) | (0.745) | (1.129) | (0.891) | (1.128) | (0.882) |
| PPVT Score | | 0.022 | | 0.025 | | 0.023 | | 0.322 | | 0.260 | | 0.284 |
| | | (0.082) | | (0.080) | | (0.081) | | (0.238) | | (0.208) | | (0.210) |
| Constant | 59.094 | 43.770 | 57.525 | 41.695 | 58.209 | 42.198 | 49.160 | 96.724 | 36.103 | 82.736 | 37.956 | 90.938 |
| | (74.993) | (76.050) | (74.564) | (75.990) | (74.698) | (76.059) | (65.560) | (66.915) | (67.680) | (71.514) | (71.186) | (74.406) |
| Joint F-test on village fixed effects (F-stat) | 4155.94 | 11050.46 | 29529.25 | 1762.60 | 17653.32 | 2729.69 | 9841.66 | 11782.26 | 5531.56 | 7216.93 | 5721.07 | 3562.83 |
| Observations | 302 | 302 | 302 | 302 | 302 | 302 | 120 | 120 | 120 | 120 | 120 | 120 |
| $R^2$ | 0.3715 | 0.3572 | 0.3745 | 0.3602 | 0.3747 | 0.3602 | 0.2830 | 0.3428 | 0.3022 | 0.3607 | 0.3038 | 0.3667 |

Cluster-robust standard errors in parentheses; * significant at 10% level; ** significant at 5% level; ***significant at 1% level.

**Table 4**. Dependent Variable: Probability of taking the maths test in round 3

| | OLS | | | Probit (marginal effects) | | |
|---|---|---|---|---|---|---|
| **Variable** | (1) | (2) Village FE | (3) Village FE | (4) | (5) Village FE | (8) Village FE |
| Maths Score Round 2 | 0.028* | -0.003 | -0.004 | 0.028** | -0.005 | -0.006 |
| | (0.014) | (0.010) | (0.009) | (0.014) | (0.012) | (0.011) |
| Age | | 0.070 | | | 0.091 | |
| | | (0.049) | | | (0.060) | |
| Male | | 0.016 | | | 0.022 | |
| | | (0.037) | | | (0.047) | |
| Rural | | -0.010 | | | -0.003 | |
| | | (0.141) | | | (0.146) | |
| Ln(Consumption/capita) | | -0.006 | | | -0.009 | |
| | | (0.040) | | | (0.050) | |
| Caregiver Ethnicity: | | 0.029 | | | 0.036 | |
| Kinh | | (0.102) | | | (0.127) | |
| Caregiver Education: | | 0.057 | | | 0.076 | |
| Primary | | (0.082) | | | (0.103) | |
| Caregiver Education: | | 0.092 | | | 0.125 | |
| Intermediate | | (0.077) | | | (0.095) | |
| Caregiver Education: | | -0.017 | | | -0.015 | |
| Secondary/Higher | | (0.091) | | | (0.118) | |
| Constant | 0.376*** | -0.758 | 0.335*** | | | |
| | (0.125) | (0.766) | (0.088) | | | |
| Joint F-test on village fixed effects (F-stat) | | 982.62 | 190.47 | | 26114.38 | 383.80 |
| Observations | 710 | 710 | 710 | 710 | 710 | 710 |
| (Pseudo) R-squared | 0.0090 | 0.2745 | 0.2604 | 0.0066 | 0.1927 | 0.1771 |

Cluster-robust standard errors in parentheses;* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

# 7 Further Robustness Tests

## 7.1 Sample Selection

Firstly, the possibility for sample selection is investigated. Ideally, a Heckman two-step approach would be employed but, due to the lack of any plausible exclusion restrictions in the data, it has not been adopted. Selection on observables is tested instead. A linear probability model is estimated to test whether the decision to take the test in round 3 was affected by the children's performance expectations, proxied by their performance in a maths test in round 2. Results are shown in Table 4. Column (1) shows evidence of selection; the coefficient of the round 2 maths score is statistically significant, indicating that a one s.d. increase in the test score raises the probability of taking the test in round 3 by 4.64% points[13]. However, column (2) shows that this is fully driven by socio-economic characteristics; controlling for these renders the round 2 maths test score statistically

[13] The sample used for this test is the 710 children that were enrolled in school in both rounds, not the total 942 children that were enrolled in round 2. This is to avoid two problems: first, it avoids the potential problem of identifying selection out of taking the test, not due to performance expectations, but merely due to not being enrolled in school. Secondly, the focus of this study is on the impact of child labour for children enrolled in school in both rounds, so considering also those not enrolled in round 3 would be misleading. The mean of the maths test score in round 2 for this sample is 7.672 and the standard deviation is 1.658. This was not included in the data description section as it is not related to the main sub-samples of interest in this study.

insignificant. In fact, column (3) indicates that just controlling for village fixed effects is sufficient for performance expectations not to matter (a test of joint significance of the village fixed effects gives an F-statistic of 190.47). Given the problematic assumptions underlying the estimation of a probability model by OLS[14], probit models were also estimated. As columns (4)-(6) show, results are the same. Since village fixed effects were included in the OLS specification, robustness to selection bias (on observables) can be attributed to the previous results.

### 7.2 Measurement Error

The measure of child labour (reported by the caregiver) is expected to have some degree of error. Whereas the true value is $l_{it}^*$, we observe $l_{it} = l_{it}^* + e_{it}$. The data includes a second measure of child labour (reported by the child), where we observe $l'_{it} = l_{it}^* + u_{it}$. This provides a valid instrument by which to correct for measurement error, since $\text{cov}(l_{it}, l'_{it}) \neq 0$ and $l'_{it}$ is mean independent of $(\varepsilon_{it+3}, e_{it})$. In the rural sample[15], the absolute value of the coefficient of hours worked increases, compared to OLS, confirming the existence of measurement error. The instrument is strong; its first-stage F-statistic is 149, while the two measures are highly correlated (0.83). The coefficient of hours worked still remains statistically insignificant, but its sign changes from negative to positive, suggesting that while measurement error is accounted for, other sources of bias still exist[16]. In the urban sample, no reliable inferences can be made as the instrument is very weak; the first-stage F-statistic is only 0.528, due to the very low correlation (0.20) of the two measures.

### 7.3 Non-Linear Effects

The functional form of the estimated specification imposes a linear effect of child labour on educational attainment. To test whether this assumption is validated, a squared term for hours worked was included. In both the rural and urban samples, this term was statistically

[14] These problems include non-normality and heteroscedasticity of the residuals, and the fact that the probability of taking the test is not bounded between 0 and 1.
[15] Results are not presented in tabular form due to lack of space.
[16] Since measurement error causes attenuation bias, correcting for it should increase the absolute value of the coefficient but not alter it sign. The change of sign indicates that other sources of bias still exist.

insignificant at the 10% level. To further test the functional form, a 'saturated model' was specified where a dummy variable was included for each hour worked[17] as follows:

$$y_{it+3} = \alpha + \beta_1 l(1)_{it} + \beta_2 l(2)_{it} \ldots + \beta_k l(k)_{it} + x'_{1it}\gamma_1 + x'_{2it}\gamma_2 + x'_{3it}\gamma_3 + x'_{4it}\gamma_4 + x'_{5it}\gamma_5 + \varepsilon_{it+3} \qquad (7)$$

The null hypothesis $H_0 : \beta_1 = \beta_2 = \ldots = \beta_k$ was then tested. Resulting p-values were 0.73 for rural and 0.27 for urban. Hence, the null hypothesis of linear effects could not be rejected at the 10% level, so the assumption of constant marginal effects of child labour was correct.

### 7.4 Instrumental Variables

The previous methods have attempted to deal with several underlying problems of the OLS specification but are insufficient to fully account for the most serious of these, endogeneity of the hours worked variable. Solving this necessitates an instrumental variables strategy. Instrumental variables must satisfy two conditions: validity (they must have no direct effect on maths scores, and are therefore validly excluded from the second stage) and relevance (they are strong predictors of hours worked). Plausible instruments already used in the literature were initially considered, such as household member shocks (e.g. illness or death) and agricultural shocks. However, these have very low incidence in the Young Lives data. As such, they fail to explain significant variation in the endogenous variable and so do not pass the relevance requirement. Common shocks affecting everyone would be more relevant.

In line with the approach of Beegle et al. (2009) who studied the impact of child labour on educational attainment using the Vietnam Living Standards Survey, community-level rice prices are employed as an instrument for hours worked. An interaction of rice prices with a household wealth indicator, the log per capita asset value, is used as a second instrument. Following Beegle et al. (2006) who show that owning household assets reduces the impact of income shocks on child labour, this interaction term is included to capture the differential ability of households to cope with a rice price shock. Richer households are

[17] L(1) is a dummy variable taking the value of 1 if child *i* worked for one hour per day, and 0 otherwise, L(2) is a dummy variable taking the value of 1 if child *i* worked for two hours per day, and 0 otherwise, etc.

more able to cope with shocks, so the impact of rice prices on child labour demand is expected to be decreasing in wealth. Thus, the following two-stage least squares specification is estimated[18]:

$$l_{it} = \alpha + \theta_1 rice\_p_{it} + \theta_2 [rice\_p * \ln(assets)]_{it} + x'_{1it}\gamma_1 + x'_{2it}\gamma_2 + x'_{3it}\gamma_3 + x'_{4it}\gamma_4 + x'_{5it}\gamma_5 + v_{it} \quad (8)$$

$$y_{it+3} = \alpha + \beta \hat{l}_{it} + x'_{1it}\gamma_1 + x'_{2it}\gamma_2 + x'_{3it}\gamma_3 + x'_{4it}\gamma_4 + x'_{5it}\gamma_5 + \varepsilon_{it+3} \quad (9)$$

This specification requires rice prices to be a good instrument for child labour (since assets are also included in the second stage, the interaction term is a good instrument as long as rice prices are). For the exclusion restriction to hold, rice prices must have no direct effect on maths scores except through their effect on hours worked. This assumption is not hard to defend; it is difficult to conceive of any plausible mechanism through which rice price fluctuations would have a direct impact on how students perform on a mathematics test three years later. Regarding relevance, rice production and consumption in Vietnam are amongst the highest globally. As such, they have a direct impact on child labour. Fluctuations in their prices have a direct income effect on households, who then adjust their child labour demand to adapt to the income shock. In rural areas, where households are net suppliers of rice, increases in rice prices allow households to reduce child labour through a positive income effect. There is also a second effect: profit incentives could induce expansion of rice cultivation, leading to higher demand for child labour. Which effect dominates has no effect on whether rice prices are relevant. In urban areas, where households are net demanders of rice, there is only an income effect: increases (decreases) in rice prices increase (decrease) the household demand for child labour.

### 7.5 Instrumental Variables Results

Table 5 presents the results. Columns (1) and (6) replicate previous OLS results to facilitate comparison. In the rural sample, the instruments are much weaker than expected. First stage results are shown in column (2). While rice prices are significant determinants of hours worked, their interaction with assets is not, resulting in a joint significance F-statistic

[18] *rice_p* stands for rice prices.

of 2.67, well below the rule of thumb of F>10[19]. Consequently, the second stage regression (column 3) results are unreliable. A possible explanation may be that the asset value is an inaccurate indicator of wealth in rural settings. Attempting to overcome this, the first stage regression was re-estimated by replacing the asset value with the area of land owned by the household, on the grounds that this may be a more appropriate wealth measure and may also be a better indicator of the ability of households to expand cultivation of rice. Column (4) presents the first stage regression results. Now, both instruments are significant determinants of hours worked. Rice price increases are associated with less child labour, implying that the profit incentive to expand production dominates the positive income effect. This is also suggested by the positive coefficient of the interaction term; increases in child labour are larger in wealthier households, possibly because owning more land enables them to expand their production more efficiently than poorer households. While the null hypothesis of the Sargan test (that both instruments are valid) cannot be rejected at the 10% level (p-value is 0.69), the instruments remain severely weak (the F-statistic is 2.29, even lower than before). Hence, again, the column (5) structural equation results are not reliable. As such, the IV results for the rural sample can only be suggestive. Importantly, we find that with both approaches, the coefficient of hours worked remains statistically insignificant, so our conclusions from OLS (column 1) remain unchanged. It cannot be inferred whether this is due to the weak instrument problem or because the true impact of hours worked in rural areas is indeed negligible.

In urban areas, results are much more robust. The first stage regression (column 7) confirms our theoretical expectations. Firstly, higher rice prices are associated with more child labour, through a negative income effect. Secondly, the coefficient on the interacted instrument is negative, showing that wealthier households, being more able to cope with income shocks, demand less increases in child labour than poorer households as a response to a shock. Importantly, the instruments are strong (the joint significance test F-statistic is 12.74), while the hypothesis of the Sargan test that both instruments are valid cannot be rejected at the 10% level (p-value is 0.85). The IV strategy is therefore successful in accounting for endogeneity in the urban sample, so the estimated structural equation (column 8) can be given a causal interpretation. The results show that child labour has a

[19] While the Stock and Yogo critical values provide a more informative basis for assessing the F-statistic than this rule of thumb, they only hold under the assumption of i.i.d errors. As the errors in the data are clustered, these critical values do not apply.

negative causal impact on maths scores; hours worked retain their statistical significance after instrumenting. Compared to the OLS estimates (column 6), the magnitude of this impact increases greatly; the loss in maths scores caused by a one s.d. increase in hours worked rises from 3.59 to 12.45 points (out of 100), which is equivalent to 67.85% of one standard deviation of the test score.

The downward bias in the absolute value of the OLS estimate can be attributed to two problems in estimating the OLS specification; unobserved ability bias and measurement error. Column (7) of table 5 shows a positive correlation between a proxy of ability (PPVT scores) and hours worked. This implies that parents are choosing to put their most able children to work, possibly because they are more productive. Not controlling for innate ability introduces omitted variable bias, creating positive bias in the estimate of the coefficient of hours worked and understating the true impact of child labour. A second explanation is attenuation bias due to measurement error. An attempt to assess this possibility was presented in Section 7.2, but no robust conclusions could be made due to a weak instrument problem.

**Table 5**. Instrumental Variables Regressions

| | Rural | | | | | Urban | | |
|---|---|---|---|---|---|---|---|---|
| | **OLS** | **IV** | | | | **OLS** | **IV** | |
| Variables | (1) Maths Score<br><br>Village FE | (2) 1st Stage: Hours of Economic Work<br><br>Village FE | (3) 2nd Stage: Maths Score<br><br>Village FE | (4) 1st Stage: Hours of Economic Work<br><br>Village FE | (5) 2nd Stage: Maths Score<br><br>Village FE | (6) Maths Score<br><br>Village FE | (7) 1st Stage: Hours of Economic Work<br><br>Village FE | (8) 2nd Stage: Maths Score<br><br>Village FE |
| Hours of Economic Work (hours/day) | 0.192 | | 2.307 | | -8.649 | -8.892** | | -30.812** |
| | (1.333) | | (7.089) | | (9.137) | (2.607) | | (15.602) |
| Age | 2.452 | 0.310* | 1.148 | 0.337* | 3.890 | -1.257 | -0.143 | -4.515 |
| | (4.052) | (0.173) | (4.731) | (0.167) | (4.880) | (3.096) | (0.097) | (4.163) |
| Male | -2.457 | 0.186 | -4.002 | 0.154 | -2.317 | -3.855 | 0.005 | -3.574 |
| | (2.339) | (0.164) | (2.602) | (0.169) | (2.965) | (3.432) | (0.063) | (2.530) |
| Long-term Illness | -10.865 | 0.105 | -11.388** | 0.049 | -10.777* | -7.366 | 0.069 | 0.498 |
| | (6.337) | (0.245) | (4.861) | (0.242) | (5.806) | (5.126) | (0.079) | (0.556) |
| BMI | 1.510*** | 0.009 | 1.615*** | 0.010 | 1.610*** | 0.304 | 0.007 | -6.173 |
| | (0.495) | (0.027) | (0.390) | (0.028) | (0.510) | (0.509) | (0.005) | (4.562) |
| Household Size | -0.075 | 0.026 | -0.032 | 0.005 | -0.039 | 1.306 | -0.020 | 0.824 |
| | (1.054) | (0.071) | (0.842) | (0.066) | (1.173) | (1.393) | (0.015) | (1.413) |
| Credit Access | -2.242 | 0.177 | -3.293 | 0.149 | -1.583 | 4.346 | -0.331 | -3.186 |
| | (3.796) | (0.132) | (3.696) | (0.125) | (3.337) | (3.949) | (0.179) | (9.687) |
| Ln(Consumption/ capita) | -1.247 | -0.401** | 0.020 | -0.461** | -5.771 | -0.992 | -0.054 | -1.885 |
| | (3.354) | (0.172) | (3.847) | (0.156) | (4.481) | (2.043) | (0.027) | (2.597) |
| Ln(Assets/capita) | -0.192 | -0.081 | -0.271 | | | -0.179 | 0.108* | -0.154 |
| | (0.331) | (0.065) | (0.262) | | | (0.132) | (0.052) | (0.101) |
| Rice price | | -0.332* | | -0.437* | | | 0.246** | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | (0.184) | | (0.215) | | | (0.083) | |
| Rice price X | | 0.016 | | | | | -0.020* | |
| Ln(Assets/capita) | | (0.013) | | | | | (0.009) | |
| Land Area | | | | -0.156 | 0.121 | | | |
| | | | | (0.101) | (0.288) | | | |
| Rice price X | | | | 0.036* | | | | |
| Land area | | | | (0.019) | | | | |
| Caregiver Ethnicity: | -7.861** | -0.049 | -7.018** | 0.025 | -8.014 | | | |
| Kinh | (3.662) | (0.553) | (3.200) | (0.559) | (5.275) | | | |
| Caregiver Education: | 5.680 | -0.368 | 0.297 | -0.461 | -3.197 | 8.262 | 0.390 | 16.369* |
| Primary | (10.265) | (0.463) | (6.745) | (0.510) | (9.955) | (7.696) | (0.116) | (9.659) |
| Caregiver Education: | 1.344 | -0.231 | -3.711 | -0.310 | -5.797 | 2.984 | 0.010 | 2.843 |
| Intermediate | (7.801) | (0.570) | (4.615) | (0.639) | (8.961) | (4.670) | (0.059) | (2.959) |
| Caregiver Education: | 7.177 | -0.365 | 1.853 | -0.412 | -2.494 | 3.463 | 0.094 | 5.163** |
| Secondary/Higher | (9.494) | (0.578) | (6.2170) | (0.665) | (11.076) | (4.814) | (0.072) | (2.478) |
| Maths Extra Classes | 0.716 | -0.038 | 0.960 | -0.043 | 0.524 | 1.739* | 0.000 | 1.735** |
| (hours/week) | (0.621) | (0.029) | (0.652) | (0.029) | (0.669) | (0.745) | (0.008) | (0.700) |
| PPVT Score | 0.022 | 0.000 | 0.131 | 0.000 | 0.159 | 0.322 | 0.011* | 0.317 |
| | (0.082) | (0.003) | (0.092) | (0.003) | (0.098) | (0.238) | (0.006) | (0.248) |
| Constant | 43.770 | -1.278 | -5.520 | -0.608 | -9.112 | 96.724 | 1.264 | 62.816 |
| | (76.050) | (2.706) | (74.534) | (2.333) | (75.320) | (66.915) | (2.611) | (82.295) |
| Joint F-test on village fixed effects (F-stat) | 11050.46 | 3579.20 | | 521.41 | | 11782.26 | 2861.32 | |
| Joint F-Test on instruments (F-stat) | | 2.668 | | 2.290 | | | 12.738 | |
| Sargan J-Test on instruments (p-value) | | 0.3210 | | 0.6874 | | | 0.8528 | |
| Observations | 302 | 302 | 302 | 302 | 302 | 120 | 120 | 120 |
| $R^2$ | 0.3572 | 0.2480 | 0.3715 | 0.2677 | 0.1183 | 0.3428 | 0.2436 | 0.2117 |

Cluster-robust standard errors in parentheses;* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

# 8 Discussion

The findings of this study differ across rural and urban areas. In rural areas, there is suggestive evidence that child labour has no significant impact on educational attainment. This result cannot be given a causal interpretation, due to a lack of strong instruments for rural child labour. However, it is unlikely that a statistically insignificant result in OLS estimation would become significant after instrumenting; the opposite is usually expected. Notwithstanding this limitation, these results suggest that child labour in rural areas does not significantly interfere with the schooling of children. This implies that working in rural areas is compatible with their learning process and does not take away time or energy that would otherwise be spent on school-related activities. Further, this result could be driven by the type of work rural children engage in. Given that few formal employment opportunities exist in rural settings, most children undertake agricultural work for the household farm. Results suggest that this form of work is not particularly harmful for children.

In contrast, there is clear, causal evidence that child labour has a large adverse impact on educational attainment for children in urban areas. This finding is robust to endogeneity of the child labour variable. This large heterogeneity in the impact of child labour across types of households justifies the initial decision to split the sample into a rural and urban sub-sample. Moreover, it suggests that the type of work is a crucial determinant of whether working is harmful for children, as work undertaken in urban settings is very different. Employment opportunities in the formal labour market are more prevalent in urban areas, indicating that this type of work is much more detrimental than agricultural activities, despite the lower mean number of child labour hours observed in urban areas. Hence, wage work is not compatible with schooling. Importantly, the finding that parents choose their more able children to work highlights that working is not compatible even for children of high cognitive ability. This indicates that policy should focus more on disincentivising parents from committing their children to formal labour, and less on reducing child labour in general; targeting reductions in the most harmful types of labour will be more effective in reducing its adverse effects.

These findings are not directly comparable to other studies of developing countries. The most relevant study on Vietnam, that of Beegle et al. (2009), considered the long-term impact of child labour on grade attainment and participation, not test scores. While they also identify a negative impact of child labour on educational outcomes, their study only considers rural households, for which we cannot infer causal results due to weak instruments. Other studies investigating test scores only consider contemporaneous effects. Nevertheless, results are similar, albeit only for the urban sample. Bezerra et al. (2009) found that working children in urban Brazil of a similar age ($8^{th}$ graders) to those in the Young Lives survey scored on average 8 points less in a maths test, which is lower than our finding but still very large. Further, Gunnarson et al. (2006) found that a one s.d. increase in hours worked led to a 16% reduction in maths test scores. Although consistent with our urban finding, this result was estimated by pooling rural and urban households across nine countries, so direct comparison is not warranted.

## 9 Conclusion

This study investigated the impact of child labour on educational attainment over a three-year horizon using an instrumental variables strategy. In rural areas, there is suggestive evidence that child labour has no effect on mathematics test scores, although this finding is limited by a weak instruments problem. In urban areas, strong instruments allow us to identify a large causal impact of child labour; a one s.d. increase in hours worked reduces test scores by 12.45 points (out of 100), or 67.85% of one standard deviation of the test score. Given the heterogeneity in the type of employment opportunities available between rural and urban areas, results indicate that policy should focus more on reducing the incidence of the most harmful types of child labour, rather than just reducing child labour in general.

This study has several limitations that could be overcome by better data. Firstly, stronger instruments are required for rural child labour. Secondly, further controls, such as school quality measures, would improve the robustness of the results. While village fixed effects partly capture differential school quality by location, objective measures such as class size would be more informative.

This study could be extended in several ways. Once future rounds of data are collected, further questions could be investigated such as the impact of child labour on final educational attainment, or employment outcomes in adulthood. Moreover, once round 3 data become publically available, the younger cohort of children surveyed by Young Lives could also be included in the analysis.

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