



YOUNG LIVES STUDENT PAPER

The Impact of Child Labour on the Educational Achievement of Children in Vietnam

Annabel Watson

June 2008

Paper submitted in part fulfilment of the requirements for the degree of MSc in Economics for Development at the University of Oxford.

The data used in this paper comes from Young Lives, a longitudinal study investigating the changing nature of childhood poverty in Ethiopia, India (Andhra Pradesh), Peru and Vietnam over 15 years. For further details, visit: www.younglives.org.uk.

Young Lives is core-funded by the Department for International Development (DFID), with sub-studies funded by IDRC (in Ethiopia), UNICEF (India), the Bernard van Leer Foundation (in India and Peru), and Irish Aid (in Vietnam).

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.

The Impact of Child Labour on the Educational Attainment of Children in Vietnam

Thesis submitted in partial fulfilment of the requirements for the
Degree of Master of Science in Economics for Development
at the University of Oxford

27th May 2008

By

Annabel Watson

Table of Contents

Abstract	3
List of Tables	4
Introduction	5
Literature Review	6
Data Description	9
Empirical Framework	13
Results	19
Discussion	22
Conclusion	23
References	24

Abstract

The incidence of child labour in the World today is very high, particularly in Third World countries and an extensive literature exists on the causes of this phenomenon. However there has been little investigation into the consequences of child labour on socioeconomic outcomes of which the educational attainment of the children is one. Using cross-section data for 12 year old children in Vietnam, collected by the Young Lives team, I use firstly OLS regressions and then an instrumental variable strategy to evaluate the impact of child labour on the test scores of the sampled 12 year olds in the Peabody Picture Vocabulary Test which I am using as a measure of their educational attainment. I have created a child labour variable by combining the total number of hours in a typical day that the child spends caring for others, doing domestic tasks, working for the family farm or business and working for pay outside of the household. I find that child labour does not have a significant impact on the test score results of the children when village level fixed effects are included, and when child labour is instrumented for using exogenous shocks to the household. The evidence suggests that the short-term impact of child labour may be negligible although this only holds for the relatively low levels of child labour undertaken by the Vietnamese children. Reducing child labour will require households to be very forward-looking and to have access to sufficient credit to fund the costs of schooling without requiring their children work.

List of Figures and Tables

Figure 1	Histogram of Child Labour Variable	10
Figure 2	Scatter Plot of Child Labour Versus Educational Attainment	11
Table 1	Descriptive Statistics	11
Table 2	OLS Regression Results	15
Table 3	Main Results	16
Table 4	First Stage Estimates, Instrumental Variables Approach	17
Table 5	2SLS Estimates Using All The Instruments	18
Table 6	Final IV Results and Robustness Checks	19

Introduction

This paper studies the effect that child labour has on the educational attainment of 12-year-old children in Vietnam. I examine whether child labour has a negative impact on the educational attainment of the children by making them perform poorly in school due to fatigue. I also test to see whether child labour has an important effect on the total hours of extra classes attended per week to investigate whether there is a work-schooling trade-off. When village level fixed effects are incorporated into the OLS regression the child labour variable becomes insignificant. It remains insignificant when an instrumental variables strategy is employed.

The assumption that child labour is harmful to children's development underpins both the theoretical literature and the policy debate¹. The general consensus from the is that global returns from the elimination of child labour would be enormous, but as yet there has been few attempts to quantifiably measure this. In this paper I examine whether child labour has an adverse effect not only through a reduction in enrolment but also because the children may be too tired to concentrate when they are in school. Labour work may displace time spent on homework or additional study, or in extra classes, which are a popular phenomenon in Vietnam.

Vietnam is one of the few countries that has seen a significant drop in poverty over the past decade, with the headcount ratio falling from 58% to 37% between 1993 and 1998 (World Bank et al). The incidence of child labour has fallen but there is growing concern about inequality. Edmonds (2001) documents that the probability that a child (aged six to fifteen) works in agriculture, a family operated business, or wage employment drops by 28% between 1993 and 1998. However poverty is increasingly concentrated in specific regions and among certain groups, of which children are the most vulnerable. The phenomenon of working children is most prevalent amongst poor families and ethnic minority children are especially likely to work. Edmonds and Turk (2003) also find that ethnic minority children and the children of recent migrants appear to remain particularly vulnerable even by the late 1990s. A number of INGO studies show that many children work in hazardous and difficult conditions due to a weak legal environment and inadequate law enforcement to protect children from exploitation.

The level of school enrolment in Vietnam is high compared to neighbouring countries at the same level of economic development. In addition, the level of female enrolment lags only slightly below that of males at primary and lower secondary school levels. However this masks regional disparities as enrolment rates are very low in the poorest and very rural north, Central Highlands and Mekong River Delta, but are higher in the richer north and more urbanised Red River Delta. These variations in enrolment rates coincide with large differences in pupil achievements across regions. An additional problem is that the academic year is short by international standards, particularly in rural areas. Consequently, most children receive only half the number of teaching hours compared with international norms. A target of the Vietnamese Government is to provide full shifts of primary education by 2015.

¹ Beegle & Dehejia (2004)

This failing of the current education system can partly explain the prevalence of extra classes in the country. The target market for extra classes consists of two groups: low score performers who enlist to enable them to catch up with their classmates, and outstandingly talented children who attend to progress beyond their peers. But recent reports from Vietnam reveal that children from poor families have been unable to access these classes because they cannot afford them, and hence extra classes have become highly controversial. It has been suggested that in Vietnam the extra classes have been manipulated by motives that are not based on real learning needs (Chau, Ry and Dam, 2000; Trang, 2002). Extra classes now serve the business motives of teachers enabling them to supplement their income.

The government had banned extra classes, which are run outside school administrations but remains commonplace for teachers to register to run home-based crèches but then hold extra classes instead. Legally recognised extra classes are intended to occupy no more than four hours a week and to cost no more than 4,000-6,000 dong (VND) per month. Forty-six per cent of children surveyed by Young Lives sites took extra classes. On average children attended extra classes for nine hours a week, with 90 per cent of those taking extra classes exceeding the legal limit of four hours a week². Extra classes did not improve writing or numeracy skills but were linked with increased reading ability implying that these extra classes are not an effective way for children to learn.

A growing empirical literature analyses the relationship between child labour and school attainment but, with a few exceptions, this literature examines the correlation, not the causal relationship, between these variables³. There are several reasons to question a causal interpretation of the impact child labour has on educational attainment. Households with children who work vary in a whole range of observable (education, wealth, occupation) and unobservable (concern for children, social networks) characteristics. The ability of the child is likely to be known to the parents but not to the econometricians, which will bias results. For example if parents send their least motivated children to work this selection bias would cause an apparent negative correlation between child labour and the educational attainment of the child.

In this paper I try to ascertain the causal relationship between child labour and school attainment. I use an instrumental variables strategy that addresses some of the limitations of selection biases associated with OLS. I experiment with a number of possible instruments: household deaths, whether the household owns any animals, whether the household has experience pests or diseases that affected crops before they were harvested in the last 4 years and whether they have experienced crop failures in the last 4 years. These variables plausibly influence child labour but are exogenous to the schooling attainment of the children. I find that child labour does not have a statistically significant effect when village level fixed effects are included in the regressions nor when instrumental variable estimation is used.

² Vietnam Preliminary Report, Young Lives website

³ Beegle & Dehejia (2004)

Literature Review

The Child Labour-educational attainment trade-off

Child labour is a facet of poverty – their connection is well entrenched in the empirical literature. The dilemma is whether this child labour is efficient from an economic point of view, and whether it is a hindrance on the child's achievements at school and personal development. The conventional argument for government intervention in child labour markets is based on the existence of externalities – parents do not fully internalise the positive externalities accruing from higher educational attainment to their children and hence under-provide in terms of education for their offspring.

Patrinos and Psacharopoulos (1995) show that factors predicting an increase in child labour also predict reduced school attendance and an increased chance of grade repetition. The authors estimate this relationship directly and show that child work is a significant predictor of age-grade distortion (see Patrinos and Psacharopoulos, 1997). Akabayashi and Psacharopoulos (1999) show that, in addition to school attainment, children's reading competence decreases with child labour hours. Finally Heady (2003) uses direct measures of reading and mathematics ability and finds a negative relationship between child labour and educational attainment in Ghana.

All of these papers examine the correlation, rather than the causal relationship between child labour and schooling outcomes. However Cavalieri (2002) use propensity score matching and finds a significant, negative effect of child labour on educational performance. Ray and Lancaster (2003) instrument child labour with household measures of income, assets and infrastructure, to analyze its effect on several school outcome variables in seven countries. But their instrumenting framework is questionable, as they make the strong assumption that household income, assets, and infrastructure are exogenous to the schooling equations.

In order to test whether child labour is efficient or not, Baland and Robinson (2000) assume that there is a trade-off between child labour and the accumulation of human capital. When parents are altruistic and child labour is known to be socially inefficient it can occur in equilibrium because parents do not fully internalise its negative effects. This arises when there are zero bequests or with imperfect human capital markets are imperfect which are common circumstances in developing countries. The authors find that child labour is inefficient when it is used by parents as a substitute for negative bequests (to transfer income from children to parents when the family is very poor); or as a substitute for borrowing due to imperfect capital markets (to transfer income from the future to the present). A marginal ban on child labour can be Pareto improving by internalising the negative externalities, even though the parents are not directly compensated.

The policy implications of child labour are not straightforward. For example an outright ban on child labour would be a substantial short-term cost to the economic welfare of the household and in very poor regions, the alternative to work may be to suffer acute

hunger or starvation. Basu and Van (1998) note that if child labour occurs because of the parent's concern about the survival of the household then the argument for banning child labour loses much of its force. In this case the labour market will be characterised by multiple equilibria with one in which wages are low and children work and another in which wages are high and children do not work. The main division in policy design is between legal interventions such as banning child labour and collaborative interventions: public action, which alters the economic environment to induce parents to withdraw the children from the labour force of their own accord. These policies may include advances in technology, improvement in the adult labour market and greater availability of good schooling.

Child labour is perceived to be a serious problem as it is believed to be destructive to children's intellectual and physical development, especially that of young children. The danger is exacerbated for those children who work in hazardous industries. This is the theory behind the 'child labour trap' – if a child is employed all through the day, the child remains uneducated and subsequently has low productivity as an adult so child labour can directly contribute to adult unemployment in developing countries. A major caveat of the literature to date is that there is very little treatment of such long-term dynamic consequences of child labour.

Psacharopoulos (1997) used household survey data from Bolivia and Venezuela to show that working children contribute substantially to household incomes, but the educational attainment of children who work is 2 years less than that of non-working children. However in contrast to this result, Patrinos and Psacharopoulos (1997) did similar research using Peruvian data which revealed that child labour was not detrimental to schooling and left the authors wondering if in some cases "working actually makes it possible for the children to go to school". It can be assumed here that this result only holds for part-time work, which is funding the cost of the education. Hence this evidence suggests that a small amount of child labour can be a complement to schooling. This is especially likely to be true in rural areas and the urban informal sector where work hours are not rigid, so can be conducted outside of the school timetable.

It is not always the poorest households that engage in child labour. While household income draws children out of school, the productivity effect of underlying greater asset holdings does the contrary⁴. Beegle, Dehejia and Gatti (2006) find that there is a positive and significant relationship between the level of household assets and the use of child labour. This is initially surprising (since child labour is normally portrayed as being negatively associated with household wealth); but in agricultural settings a positive association can be rationalised. Rural households with larger farms are more likely to demand higher levels of child labour from their children. In Vietnam, evidence suggests that the opening and closing of household enterprises is associated with increases in child labour⁵.

⁴ Cockburn & Dostie (2007)

⁵ Edmonds & Turk (2003)

Existing work on Vietnam

Rapid economic growth in Vietnam in the 1990s has coincided with a substantial decline in child labour (Rosati and Tzannatos, 2004). Edmonds and Turk (2003) document this sharp decline in the 1990s and link it to significantly improved living standards. Beegle and Dehejia (2004) use panel data from Vietnam and an instrumental variable strategy to evaluate the effect of child labour participation on outcomes over a five-year horizon. They find significant negative impacts of child labour on subsequent school participation and educational attainment. Beegle, Dehejia and Gatti (2004) also evaluate the causal effect of child labour participation on socio-economic outcomes such as education, wages and health, again using panel data and an instrumental variables strategy. They observe substantially higher earnings for those adults who worked as children. Over a longer horizon, they estimate that from age 30 onward the foregone earnings attributable to lost schooling exceed any earnings gain associated with child labour.

Data Description

I use data collected by the Young Lives team in Vietnam during the second round of quantitative data collection in 2006/7 for the older cohort of children. This is a cross-section from a panel dataset based on individuals in different households. Young Lives is an innovative long-term international research project investigating the changing nature of childhood poverty⁶. Young Lives is tracking the development of 12,000 children in Ethiopia, India (Andhra Pradesh), Peru and Vietnam through quantitative and qualitative research over a 15-year period. Since 2002, they have been following two groups of children: 2000 children in each country who were aged between 6 months and 17 months in 2002 and 1000 children in each country aged between 7.5 years old and 8.5 years old in 2002. These countries were chosen to encompass the wide range of cultural, political, geographical and social contexts in which children grow up. They also experience issues, which are common to developing countries, such as high debt burden, post-conflict reconstruction, and environmental disasters such as drought and flood.

In this paper I am using data from the child questionnaire and the household questionnaire for caregivers of 11-12 year-old children. The child questionnaire provides detailed information on the daily activities of the children. In order to create my independent 'child labour' variable I have summed 4 variables in the dataset to create an overall daily measure of the level of child labour undertaken by the each child. This is measured in hours and comprises the time spent by the child caring for others (younger siblings, ill household members), on domestic tasks (fetching water, firewood, cleaning, cooking, washing, shopping), on the tasks on the family farm (cattle herding, other family businesses, shepherding etc) and finally on activities for pay outside the household or for someone not in the household. I have included chores in my definition of child labour because the concept of child labour (by ILO standards) is not restricted to economic activities⁷. There is a 'CHLDWORK' variable in the literature, but it is not a suitable measure of child labour levels as it is a simple binary variable which asks the

⁶ Young Lives website

⁷ Beegle, Dehejia, Gatti (2006)

child if they have done anything in the last 12 months to get money or things for themselves or their families. Because most developing countries lack a smoothly functioning child labour market, the majority of child labour is likely to be undertaken for the child's own household so it is a serious underestimate to just denote paid work outside the household as labour.

Young Lives assesses the educational abilities of the children with a number of numeracy, literacy and mathematical tests. A useful gauge of the overall educational attainment of the children is the PPVT test, which measures ability across a broad spectrum of attributes. I use the total mark achieved in this test as my measure of the educational attainment of each child. The PPVT (Peabody Picture Vocabulary Test) consists of 17 sets of 12 words each. Children start the test at a particular set depending on their age and then move up or down depending on their responses. As the children surveyed are all the same age I am comparing their raw score test results as there is no need to standardise for age variation. Raw score test results can take possible values from 0 to 204.

I then consider all the factors that I wish to control for in my regressions. I have created a dummy variable, WORSE which picks up whether the child's health is worse than that of children of the same age. I would expect more sickly children to perform more poorly at school. I also created an earnings variable as I anticipate higher earnings will positively impact on test results. This is because richer households will require lower levels of child labour and in addition these households have the capacity to pay for extra classes for the child if necessary. I summed the total amount received by each household in the last 12 months in the form of earnings, cash and receipts in-kind. I then included the log of earnings in my regressions as I think that the returns to earnings are unlikely to be linear (consensus in the literature). In addition to earnings I computed an 'ASSETS' variable by summing the total number of tractors, items of farm equipment, sewing machines, televisions, radios, cars/trucks/automobiles, motorbikes/scooters, bicycles, landline telephones, mobile/cell telephones, refrigerators, electric ovens, tables and chairs, sofas, fans and beds owned by each household.

I summed the total hours each child spends in extra classes for various subjects into a total extra classes variable, 'TOTEXTCLSS'. I created 3 region dummies to account for the 4 main regions surveyed in Vietnam: the Northern Uplands, the Red River Delta, the Mekong River Delta and the Central Coastal. I also created an urban dummy to distinguish between urban and rural areas. To examine whether child labour is having an impact on test scores through reduced classroom time, I run a regression with the 'TOTEXTCLSS' variable as my dependent variable. This will verify whether there is a schooling-work trade-off in operation.

The level of child labour in Vietnam is relatively low, and as the scatter plot shows it does not appear to be noticeably linked to the educational attainment of the children. The incidence of work outside of the family enterprises is rare and although the majority of children are involved in some domestic chores these do not occupy a considerable amount of their time. 81.11% of the children work between 0 and 3 hours per day. Enrolment in Vietnam is very strong with 99% of the children surveyed currently attending school. Although Vietnamese children are more literate than many of their

peers in countries at similar levels of development there remains room for improvement amongst certain groups. Children in rural communities fair on average 10% worse than their urban counterparts and less than half of the poorest children are able to write to the level expected for their age⁸.

Figure 1: Histogram of Child Labour Variable

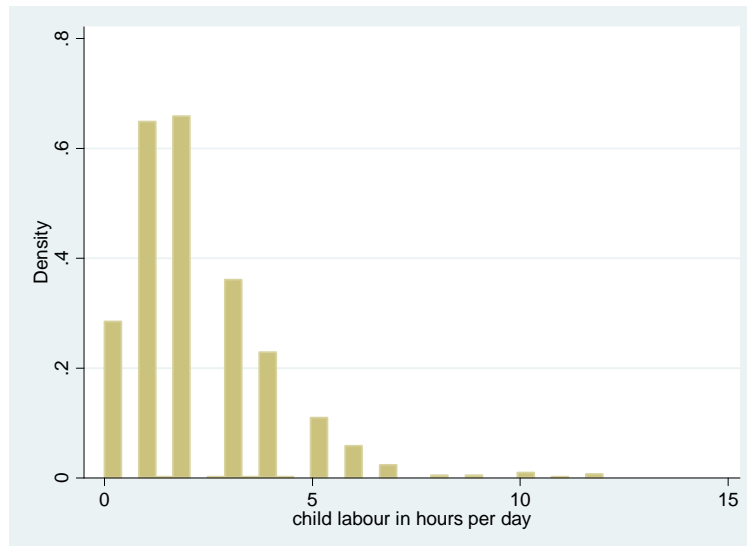
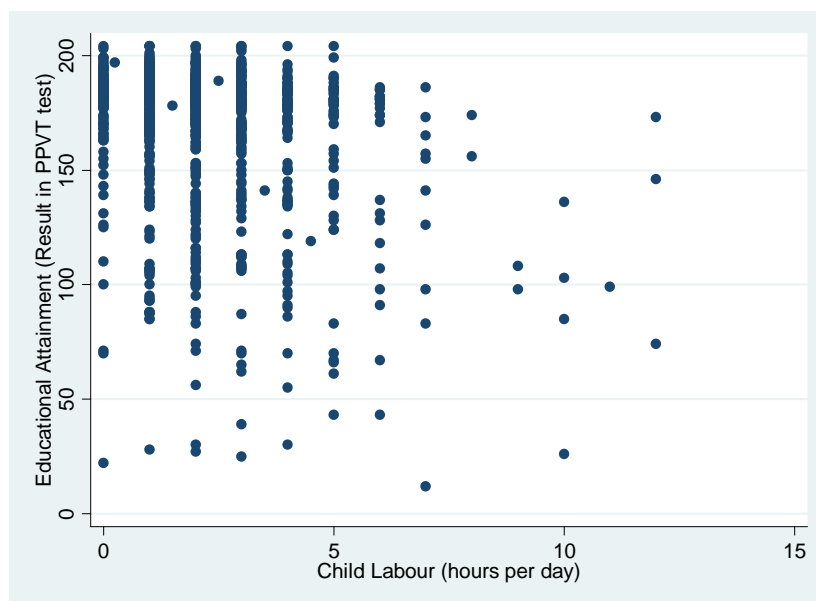


Figure 2: Scatter Plot of Child Labour Versus Educational Attainment



⁸ Vietnam country summary, Young Lives website

Table 1: Descriptive Statistics

	Full sample: all levels of child labour	Child labour \leq 2 hours per week	Child labour $>$ 2 hours per week
SEX Sex of Child	Male: 496 Female: 494	Male: 348 Female: 306	Male: 148 Female: 188
EVERSCH Ever attended formal school	No: 3 Yes: 987	No: 1 Yes: 653	No: 2 Yes: 334
ENRSCH Currently enrolled in school	No: 31 Yes: 956	No: 4 Yes: 649	No: 27 Yes: 307
SCTYPE Type of school child is attending	Private: 3 NGO/Charity/Religious:1 Public (Government): 950	Private: 2 NGO/Charity/ Religious: 1 Public (Gov): 644	Private: 1 Public (Gov): 306
MISSCH Missed more than 1 week of school	No: 931 Yes: 25	No: 630 Yes: 19	No: 301 Yes: 6
VNEXCLSS Attended extra classes in last 6 months	No: 434 Yes: 522	No: 131 Yes: 251	No: 179 Yes: 128
CSLEEP Hours sleeping on a typical night	8.772 (0.948)	8.832 (0.965)	8.655 (0.904)
WRKINJ Seriously injured while working during last 4 years	No: 940 Yes: 46	No: 624 Yes: 28	No: 316 Yes: 18
CONDPP Were conditions for PPVT adequate	No: 9 Yes: 980	No: 7 Yes: 646	No: 2 Yes: 334
WORSE Does child have worse health compared to others of age?	No: 789 Yes: 198	No: 509 Yes: 142	No: 280 Yes: 56
CFOODTOT Number of times eaten in last 24 hours	4.035 (1.080)	4.162 (1.099)	3.789 (0.996)
CGRDLIKE Education grade child would like to achieve	13.326 (1.428)	13.420 (1.310)	13.127 (1.634)
TOTEXTRCLSS Total hours of extra classes attended per week	3.971 (5.067)	4.65 (5.075)	2.650 (4.792)
type_dummy1 Is household urban?	No: 786 Yes: 204	No: 486 Yes: 168	No: 300 Yes: 36
reg_dummy1 Is household in Northern Uplands?	No: 793 Yes: 197	No: 566 Yes: 88	No: 227 Yes: 109
reg_dummy2 Is household in Red River Delta?	No: 787 Yes: 203	No: 523 Yes: 131	No: 264 Yes: 72
reg_dummy3 Is household in Mekong River Delta?	No: 600 Yes: 390	No: 476 Yes: 327	No: 215 Yes: 121
DADED What is highest education grade completed by father?	10.607 (15.625)	10.976 (15.690)	9.890 (15.497)
MUMED What is highest education grade	7.586	7.881 (8.084)	7.012 (9.433)

completed by mother?	(8.571)		
CAREED What is highest education grade completed by caregiver?	6.983 (5.026)	7.422 (5.411)	6.128 (4.050)
OWNLAND In last 12 months has anyone in household owned, sharecropped in, borrowed or rented any land in last 12 months?	No: 0 Yes: 987	No: 0 Yes: 652	No: 0 Yes: 335
ANIMALS Has anyone in household owned livestock in last 12 months?	No: 485 Yes: 505	No: 375 Yes: 279	No: 110 Yes: 226
DEBT Do you have any serious debts?	No: 407 Yes: 582	No: 282 Yes: 371	No: 125 Yes: 211
MIGHTDIE Has child been seriously ill/injured in last 4 years when he/she might have died?	No: 934 Yes: 56	No: 612 Yes: 42	No: 332 Yes: 14
LONGTERM Does child have any long-term health problems?	No: 872 Yes: 117 Missing: 1	No: 569 Yes: 84	No: 303 Yes: 33
FOODSHRT Has household had any food shortages in last 12 months?	No: 903 Yes: 87	No: 603 Yes: 51	No: 300 Yes: 36
GROSS_EARN Gross household earnings/cash/value in-kind received in last 12 months in VND 1 US Dollar = 16,470 Vietnamese Dong	0: 45 1-5000: 243 5001-10000: 136 10001-20000: 229 20001-50000: 271 50001-100000: 55 100001-250000: 11	0: 23 1-5000: 126 5001-10000: 78 10001-20000: 162 20001-50000: 208 50001-100000: 49 100001-250000: 8	0: 22 1-5000: 117 5001-10000: 58 10001-20000: 67 20001-50000: 63 50001-100000: 6 100001-250000: 3
ASSETS Assets of Household	0: 1 1-50: 929 51-100: 3 101-123: 14	0: 0 1-50: 614 51-100: 2 101-123: 10	0: 1 1-50: 315: 51-100: 1 101-123: 4

Empirical Framework

The treatment in my analysis is defined as the number of hours of child labour undertaken per day by the child, T_i . The outcome of interest (Y_i) is the test result of the child in the PPVT test. Thus my basic specification is of the form:

$$Y_i = \alpha + \beta T_i + \gamma X_i + \epsilon_i$$

where X_i are household level controls and village level fixed effects. The sample of children I examine are aged between 11.5 years and 12.5 years in 2006/7 when the survey is conducted (i.e. they are born in 1994). The survey covers 990 children over all the main districts in Vietnam. The prevalence of children working for pay outside of the household is low for this age group so my measure of child labour includes any work undertaken by the child within the household or on the family farm.

I start by running a basic OLS regression of my child labour variable that I have created on the educational attainment outcome of interest (raw score in PPVT test). I then test the robustness of this result by controlling for a number of exogenous factors that may affect the performance of the individual child such as their aspirations, the hours of extra classes they attend and the amount of sleep they have. There are two potential sources of selection bias using OLS: between-household selection (which types of households opt into child labour) and within household-selection (which children parents select to work more or less)⁹. To address the first I can control for a range of household characteristics such as parental education and debt level. Cockburn and Dostie (2007) used a simple agricultural household model with a missing labour market to show that household asset portfolios and household composition are the principal determinants of child labour demand. Because of this I have controlled for household assets in my regressions and included an urban dummy.

I also allow for common village level characteristics in an individual based equation through the use of fixed effects to obtain estimates that control for these time invariant unobservable characteristics of villages. This is useful as if for example there was an exceptionally good school in one region, this would bias upward the test scores of children within this region compared to scores of children in another region with similar child labour levels. Regional effects can also be accounted for through the use of a region dummy. The use of fixed effects will make my econometric results more credible as it will isolate the true impact of child labour on the educational attainment of the children by removing household characteristics or socio-economic factors which may also impact on their test scores. The specification for the village level fixed effects is:

$$Y_i = \alpha + \beta T_i + \gamma X_i + \varepsilon_i$$

This can be used as a final robustness check. In principle, the instrumental variables approach addresses both source of bias (between- and within- household selection), but also potentially results in misspecification error if the instruments are invalid. In contrast, the use of fixed effects corrects only for the first source of bias so are less open to misspecification.

If the child labour variable is endogenous i.e. it is correlated with unobservable factors that cannot be measured and hence are incorporated into the residual then my estimates will be biased and inconsistent. To address this problem I use an instrumental variables strategy to ‘purge’ the endogenous variable of the part that is correlated with the residual in the structural equation. The ideal instrument is one that induces variation in

⁹ Beegle & Dehejia (2004)

child labour but has no impact on the outcome of interest (educational attainment). My instrumental variable specification is: $T_i = a + bZ_i + cX_i + v_i$

$$Y_i = \alpha + \beta\hat{T}_i + \gamma X_i + \varepsilon_i$$

where in the second equation I have made the necessary two-stage least squares adjustment.

I consider a number of possible instruments. Firstly I created a dummy variable (CLINSTRUMENT) that takes an outcome of 1 for children in a household which has suffered a death of a household member in the last 4 years, and 0 for those which have not. I predict this variable will be correlated with child labour, as if the household had suffered the death of a family member then the child is more likely to have to work longer hours to accommodate for this loss. In order for the instrument to be valid it needs to be exogenous to the educational attainment of the child which this instrument is as the death is random.

For my second instrument I use the ANIMALS variable (Have you or anyone in the household owned any cows (modern variety) in the last 12 months?). Although this could be argued to be a measure of poverty I believe that it is more connected with the technology level of the household and whether it is in an urban or rural site. Therefore it is exogenous to the educational attainment of the child and is a valid instrument.

Households with more animals are likely to demand a higher level of labour on the farm from their children. I have also created another variable labelled 'INSTRUMENT', which combines the events which ask whether the household has been a victim of various forms of theft in the last four years. The variable is a dummy variable which is positive if any of events 1 to 5 are positive i.e. if the household has been a victim of the destruction or theft of tools or inputs, theft of cash, theft of crops, theft of livestock, or theft or destruction of housing or consumer goods. If the household has been a victim of any form of theft, this is a negative income shock so I would expect the demand for child labour to increase given its close association with poverty.

I also consider two other exogenous shocks to the household as instruments. Firstly EVENT28 asks whether the household has experienced pests or diseases that affected crops before they were harvested in the last 4 years. EVENT29 asks the household whether they have experienced crop failures in the last 4 years. Both of these events are unanticipated by the household, hence valid exogenous instruments and should result in increased child labour.

I use an over-identification test to see which of my instruments are valid.

If endogeneity is in fact not a problem instrumental variable estimation will be consistent (provided the instruments are correlated with the regressors and uncorrelated with the residual in the structural equation), but inefficient (i.e. higher variance than for OLS), given that OLS is valid. I use a Hausman test to check for this.

Table 2: OLS Regression Results

	(1)	(2)	(3)
	Raw Score		
Child labour in hours per day	-4.986	-1.868	-1.09
	(8.72)**	(3.09)**	(1.88)
Ever attended formal school		0.000	0.000
		(.)	(.)
Currently enrolled in school		0.000	0.000
		(.)	(.)
Type of school child is attending		-2.726	1.082
		(0.33)	(0.14)
Missed more than 1 week of school		1.495	4.414
		(0.26)	(0.84)
Total hours per week in extra classes		0.506	0.455
		(2.07)**	(1.98)*
Hours sleeping on a typical night		-2.903	-1.703
		(3.16)**	(1.98)*
Seriously injured while working in last 4yrs		0.105	-1.502
		(0.03)	(0.38)
Were conditions for PPVT adequate		36.684	29.744
		(3.57)**	(3.11)**
Sickness compared to others of age		-1.557	-0.288
		(0.74)	(0.15)
Number of times eaten in last 24hrs		-1.140	0.436
		(1.40)	(0.53)
Education grade you would like to complete		6.447	5.381
		(9.73)**	(8.60)**
Log of gross household earnings			0.437
			(0.68)
REGION==Northern Uplands			4.795
			(1.66)
REGION==Red River Delta			11.434
			(4.20)**
REGION==Central Coastal			-7.164
			(2.86)**
TYPESITE==Urban			12.140
			(4.62)**

Father's education level			-0.008 (0.15)
Mother's education level			0.063 (0.64)
Caregiver's education level			1.643 (6.67)**
Has household owned any land in the last 12 months?			0.000 (.)
Has the household owned any livestock in the last 12 months?			-7.103 (3.76)**
Do you have any serious debts			-0.573 (0.36)
Serious illness or injury in last 4 yrs			3.285 (0.91)
Child has long term health problems			0.067 (0.29)
Has household had any food shortages in last 12 months			-7.139 (2.32)*
Constant	177.679 (109.63)**	68.444 (2.24)**	67.703 (2.36)*
Observations	986	899	896
R-squared	0.07	0.20	0.33

Absolute value of t statistics in parentheses

* significant at 5%; ** significant at 1%

Table 3: Main Results

	Raw Score	Total Hours of Extra Classes	Raw Score (village level fixed effects)
Child labour in hours per day	-1.210 (2.00)*	-0.315 (2.73)**	-0.090 (1.77)
Sex of child	-2.168 (1.32)	0.376 (1.20)	-3.533 (2.36)*
Hours sleeping on a typical night	-2.903 (2.12)*	-0.250 (1.44)	-1.099 (1.30)
Seriously injured while working in last 4yrs	-0.290 (0.07)	-1.312 (1.69)	-1.537 (0.42)
Were conditions for PPVT adequate	23.325 (2.21)*	1.527 (0.75)	28.355 (2.97)**
Worse health compared to others of age	0.513 (0.25)	0.021 (0.05)	-1.519 (0.83)
Education grade you	5.293	0.349	4.678

would like to complete				
	(8.09)**	(2.85)**	(7.51)**	
Log of gross household earnings	1.182	0.174	0.411	
	(1.85)	(1.42)	(0.68)	
REGION==Northern Uplands	3.737	0.210	-6.470	
	(1.27)	(0.37)	(0.44)	
REGION==Red River Delta	10.429	2.629	9.837	
	(3.97)**	(5.23)**	(0.72)	
REGION==Central Coastal	-5.534	1.386	0.944	
	(2.15)*	(2.82)**	(0.06)	
TYPESITE==Urban	12.739	3.024	6.078	
	(7.60)**	(6.17)**	(0.73)	
Caregiver's education level	1.728	0.170	1.459	
	(7.60)**	(3.90)**	(6.85)**	
Household Assets	0.011	0.012	0.010	
	(0.18)	(1.00)	(0.17)	
Constant	71.723	-4.381	79.582	
	(0.18)	(1.29)	(4.12)**	
Observations	861	865	861	
R-squared	0.30	0.24	0.27	

Absolute value of t statistics in parentheses

* significant at 5%; ** significant at 1%

Table 4: First Stage Estimates, Instrumental Variables Approach

Instrument Used:	INSTRUMENT ANIMALS		EVENT28	EVENT29	CLINSTRUMENT
COEFFICIENT	reg2	reg3	reg4	reg5	reg1
	RAWSCR	RAWSCR	RAWSCR	RAWSCR	RAWSCR
CHLABOUR	-25.23**	-3.143	4.545	-0.719	74.95
	(10.59)	(17.07)	(6.042)	(5.053)	(241.7)
SEX	7.156	-1.417	-4.402	-2.359	-31.73
	(4.945)	(6.826)	(2.901)	(2.546)	(94.09)
LNGROSS_EARN	-2.981	0.847	2.180*	1.267	14.38
	(2.124)	(3.027)	(1.240)	(1.080)	(41.98)
CSLEEP	-6.761**	-2.311	-0.762	-1.822	13.42
	(2.622)	(3.557)	(1.542)	(1.358)	(48.86)
WRKINJ	8.378	0.408	-2.366	-0.467	-27.77
	(7.824)	(7.377)	(4.770)	(4.427)	(89.04)
CONDPP	31.02*	23.94**	21.48*	23.17**	-1.060
	(18.22)	(11.96)	(11.29)	(10.70)	(90.54)
WORSE	-3.060	0.226	1.369	0.586	11.84
	(3.751)	(3.247)	(2.299)	(2.148)	(37.05)
CGRDLIKE	3.988***	5.188***	5.605***	5.319***	9.428
	(1.247)	(1.136)	(0.762)	(0.709)	(13.44)
reg_dummy1	27.69**	5.665	-2.003	3.247	-72.22
	(11.64)	(17.27)	(6.744)	(5.804)	(241.4)

reg_dummy2	23.62*** (7.303)	11.49 (9.739)	7.268* (4.306)	10.16*** (3.809)	-31.40 (133.3)
reg_dummy3	16.33 (10.54)	-3.774 (15.74)	-10.77* (6.100)	-5.981 (5.239)	-74.85 (220.3)
type_dummy1	-9.699 (10.76)	10.93 (16.15)	18.11*** (6.225)	13.20** (5.339)	83.88 (226.0)
CAREED	1.400*** (0.411)	1.702*** (0.326)	1.806*** (0.253)	1.735*** (0.238)	2.766 (3.446)
ASSETS	-0.150 (0.128)	-0.00159 (0.131)	0.0500 (0.0774)	0.0147 (0.0713)	0.522 (1.646)
Constant	191.3*** (60.63)	81.35 (86.86)	43.07 (35.36)	69.28** (30.74)	-307.5 (1206)
Observations	861	861	861	861	861
R-squared	.	0.292	0.225	0.300	.
Standard errors in parentheses	***p<0.01	**p<0.05	*p<0.1		

Table 5: 2SLS Using All the Instruments

First-stage regressions

Source	SS	df	MS	Number of obs = 861		
Model	462.407966	18	25.6893314	F(18, 842) =	14.96	
Residual	1445.75638	842	1.71705033	Prob > F	= 0.0000	
				R-squared	= 0.2423	
				Adj R-squared	= 0.2261	
Total	1908.16434	860	2.21879575	Root MSE	= 1.3104	

CHLABOUR	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
SEX	.3626684	.0916181	3.96	0.000	.1828418	.5424951
LNGROSS_EARN	-.120161	.0374023	-3.21	0.001	-.1935737	-.0467483
CSLEEP	-.2037629	.0506143	-4.03	0.000	-.303108	-.1044179
WRKINJ	.3264209	.2270527	1.44	0.151	-.1192349	.7720768
CONDPP	.296233	.5949706	0.50	0.619	-.8715665	1.464033
WORSE	-.1614662	.1133109	-1.42	0.155	-.3838713	.0609388
CGRDLIKE	-.0659723	.03696	-1.78	0.075	-.1385169	.0065722
reg_dummy1	.8274906	.1665646	4.97	0.000	.50056	1.154421
reg_dummy2	.5093543	.1492948	3.41	0.001	.2163207	.8023878
reg_dummy3	.9435967	.1414077	6.67	0.000	.6660437	1.22115
type_dummy1	-.8181772	.144291	-5.67	0.000	-1.101389	-.534965
CAREED	-.0140131	.0127848	-1.10	0.273	-.0391069	.0110808
ASSETS	-.0065661	.0035241	-1.86	0.063	-.0134831	.0003509
CLINSTRUMENT	-.0469938	.2288797	-0.21	0.837	-.4962354	.4022479
INSTRUMENT	-.1500493	.1243528	-1.21	0.228	-.3941271	.0940285
ANIMALS	.2627803	.1098644	2.39	0.017	.0471401	.4784204
EVENT28	.3929364	.1668848	2.35	0.019	.0653773	.7204955
EVENT29	.4058849	.1456139	2.79	0.005	.1200761	.6916937
_cons	4.532982	.9988009	4.54	0.000	2.57255	6.493414

Instrumental variables (2SLS) regression

Source	SS	df	MS	Number of obs = 861		
Model	168794.238	14	12056.7313	F(14, 846) =	24.31	
Residual	489715.584	846	578.860028	Prob > F	= 0.0000	
				R-squared	= 0.2563	
				Adj R-squared	= 0.2440	
Total	658509.821	860	765.709094	Root MSE	= 24.06	

RAWSCORE	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CHLABOUR	-5.622902	3.617116	-1.55	0.120	-12.72248	1.476671
SEX	-.4547831	2.183837	-0.21	0.835	-4.741157	3.831591
LNGROSS_EARN	.41738	.903665	0.46	0.644	-1.356308	2.191068
CSLEEP	-2.810614	1.179152	-2.38	0.017	-5.125021	-.4962073
WRKINJ	1.302779	4.357576	0.30	0.765	-7.250149	9.855707
CONDPP	24.73819	10.96206	2.26	0.024	3.222152	46.25422
WORSE	-.1433272	2.141993	-0.07	0.947	-4.347572	4.060917
CGRDLIKE	5.053068	.7016436	7.20	0.000	3.675902	6.430235
reg_dummy1	8.138077	4.671834	1.74	0.082	-1.031668	17.30782
reg_dummy2	12.85349	3.342721	3.85	0.000	6.292493	19.41449
reg_dummy3	-1.51731	4.186934	-0.36	0.717	-9.735308	6.700687
type_dummy1	8.615583	4.246853	2.03	0.043	.2799785	16.95119
CAREED	1.667708	.2394915	6.96	0.000	1.19764	2.137775
ASSETS	-.0182326	.0690542	-0.26	0.792	-.1537702	.117305
_cons	93.69856	25.60833	3.66	0.000	43.43525	143.9619

Instrumented: CHLABOUR
 Instruments: SEX LNGROSS_EARN CSLEEP WRKINJ CONDPP WORSE CGRDLIKE
 reg_dummy1 reg_dummy2 reg_dummy3 type_dummy1 CAREED ASSETS
 CLINSTRUMENT INSTRUMENT ANIMALS EVENT28 EVENT29

overid

Tests of overidentifying restrictions:
 Sargan N*R-sq test 16.708 Chi-sq(4) P-value = 0.0022
 Basman test 16.662 Chi-sq(4) P-value = 0.0022

Table 8: Final IV Results and Robustness Checks

IV (2SLS) estimation

Total (centered) SS	= 658509.8211	Number of obs =	861
Total (uncentered) SS	= 25631932	F(14, 846)	=25.08
Residual SS	= 471585.6102	Prob > F	0.0000
		Centered R2	= 0.2839
		Uncentered R2	= 0.9816
		Root MSE	= 23.4

RAWSCORE	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
CHLABOUR	1.493916	4.163777	0.36	0.720	-6.666938	9.654769
SEX	-3.217346	2.29337	-1.40	0.161	-7.71227	1.277577
LNGROSS_EARN	1.65085	.9599965	1.72	0.085	-.2307081	3.532409
CSLEEP	-1.376567	1.231618	-1.12	0.264	-3.790493	1.03736
WRKINJ	-1.265445	4.314221	-0.29	0.769	-9.721162	7.190272
CONDPP	22.45936	10.68693	2.10	0.036	1.513367	43.40535
WORSE	.9155319	2.109749	0.43	0.664	-3.2195	5.050564
CGRDLIKE	5.439527	.6931354	7.85	0.000	4.081006	6.798047
reg_dummy1	1.040147	5.057958	0.21	0.837	-8.873269	10.95356
reg_dummy2	8.944258	3.473964	2.57	0.010	2.135414	15.7531
reg_dummy3	-7.995005	4.549098	-1.76	0.079	-16.91107	.9210627
type_dummy1	15.2638	4.625096	3.30	0.001	6.198775	24.32882
CAREED	1.764719	.234929	7.51	0.000	1.304266	2.225171
ASSETS	.0295279	.0688129	0.43	0.668	-.1053428	.1643986
_cons	58.26046	27.26584	2.14	0.033	4.820389	111.7005

Anderson canon. corr. LR statistic (underidentification test): 18.452
Chi-sq P-val = 0.0001

Cragg-Donald F statistic (weak identification test): 9.152
Stock-Yogo weak ID test critical values: 10% maximal IV size 19.93
15% maximal IV size 11.59
20% maximal IV size 8.75
25% maximal IV size 7.25

Source: Stock-Yogo (2005). Reproduced by permission.

Sargan statistic (overidentification test of all instruments): 0.588
Chi-sq P-val = 0.4431

Instrumented: CHLABOUR
Included instruments: SEX LNGROSS_EARN CSLEEP WRKINJ CONDPP WORSE CGRDLIKE reg_dummy1 reg_dummy2 reg_dummy3 type_dummy1 CAREED ASSETS
Excluded instruments: EVENT28 EVENT29

Results

OLS

I begin by discussing the OLS relationship between child labour and educational attainment. Though I do not believe that these estimates are causal, they are a useful reference point for my subsequent instrumental variables results. In all the OLS regressions child labour is negative and significant but the magnitude of the coefficient falls when a greater number of controls are included in the regression. However the results do run in the expected direction: higher levels of child labour result in lower educational attainments. Having suitable test conditions, the aspirations of the child and

a higher education level of the child's carer positively impact on the child's test scores. These variables are all very statistically significant as they have large t values. Having appropriate test conditions has the greatest economic significance as the coefficient is large which is to be expected, although the standard error is also large. This suggests that this has been imprecisely measured. Increased hours of sleep seem to have a negative impact on the educational attainment. This is an unexpected result but looking at the data, some children are reporting 12 hours of sleep a night so possibly some of the hours can be attributed to unproductive activities. Two of the region dummies are highly significant as is the urban dummy. This suggests that regional effects play a substantial impact on the educational achievement results. The OLS regression is explaining 30% of the variation in educational outcomes of the children. This implies that there are a lot of factors impacting on this variable that have so far not been accounted for.

I also investigate the effect of controlling for the enrolment variables in my OLS regression. I find that when I control for whether the child has ever attended school, whether he/she is currently enrolled in school and the total number of hours per week spent in extra classes the effect on the size of the child labour coefficient is minimal. The coefficient of child labour is reduced from -1.21 to -1.18 when these variables are included. Again the most statistically significant variables are the aspirations of the child and the education level of the child's carer, with appropriate test conditions being the most economically significant. The variables ENRSCH and EVERSCH (whether the child is currently enrolled in school and whether they have ever attended formal school) have been dropped from the regression showing that these variables are closely correlated with variables I have already included in my regression so there is no need to include them. The variable 'TOTEXTCLSS' has a very small magnitude and is insignificant so I have not included it in the rest of my regressions. This shows that extra classes are not having a substantial impact on the educational attainment of the children. This is a surprising result revealing the inefficiency of the education system in Vietnam.

Child labour is not having an impact on school enrolment, as enrolment of school age children in Vietnam was 99% at the time of the survey. This may explain why child labour is not having a significant impact on test scores, as there is no apparent trade-off between work and schooling. Child labour is having a highly statistically significant negative effect on the total number of extra classes attended per week but the magnitude of this coefficient is small implying that it is not an important determinant of extra classes. Also as the effectiveness of these classes has been strongly contested, this finding is still complementary to child labour having a non-significant effect on test scores.

OLS with community level fixed effects

When village level fixed effects are included in the regression, the child labour variable becomes insignificant and the magnitude of the negative coefficient is very small. This shows that it is having little impact on the test score results of the children. The sex of the child, test conditions, aspirations of the child and education level of the carer all remain significant. Village fixed effects are very important as the regression shows that

31% of all the variation in the outcome variable can be explained by these village level fixed effects, controlling for all the other variables included in the regression. Child labour it seems is not having a significant influence on the educational attainment of the children. Other factors have a far greater impact on test scores.

Instruments: First stage

The 'CLINSTRUMENT' and 'INSTRUMENT' instrument variables are individually not significant and are not strongly correlated with child labour as I had hoped and are therefore not appropriate instruments. The ANIMALS instrument is individually highly significant but also not particularly correlated with child labour so the weak instrument problem may become a factor if I was to use this instrument. The EVENT28 and EVENT29 instruments are by far the most successful instruments as they are both highly individually significant and more strongly correlated with child labour.

Instruments: Second stage

As I have more than one instruments, I can subject my set of instruments to an over-identification test. When all the instruments are used the Basman test has a P-value of 0.0022, which is very small and hence evidence against the null hypothesis indicating that some of the instruments need to be dropped. When the two event instruments are used together the P-value of the Basman test is much higher (0.4472) so this is the optimal combination of instruments. These two instruments used together remain both highly significant and correlated with child labour. The IV second stage results show that using the instruments child labour is positively correlated with educational attainment but it is no longer significant at the 5% level.

Main Results

My OLS results show that a child who increases their child labour levels from 0 to 1 hour per day will obtain a test score which is 21% of a standard deviation lower compared to if they had remained not working. This effect is significant at the 5% level. However when village level fixed effects are included in the regression the child labour variable becomes insignificant and the magnitude of the coefficient is very small. My IV results also show that child labour is not significant at the 5% level and suggest that child labour may positively impact on educational outcomes. This implies that the OLS results are downward biased. If families send their less academically talented children to work, then this selection bias will overestimate the impact of child labour on schooling attainment relative to the causal effect (as estimated by IV). This explains why the OLS results find a significant negative effect of child labour, whereas the IV results do not.

The IV results show that child labour levels in Vietnam are not having a strong impact on the educational attainment of the children. Other factors are far more important in determining the test scores of each individual child such as the aspirations of the child, the test conditions, the educational attainment of the child's carer, whether the child is living in an urban area and the region of residence as all these factors remain highly significant. Implementing the Hausman test reveals that my OLS results are

significantly different from the instrumental variable approach therefore child labour is endogenous and the OLS estimates are biased. I have also subjected my IV results to a number of robustness checks. The 'ivreg2' command in STATA automatically reports tests of both under-identification and weak identification. The Anderson (1984) canonical correlations test is a likelihood-ratio test of whether the equation is identified, i.e., that the excluded instruments are "relevant", meaning correlated with the endogenous regressors¹⁰. The null hypothesis of the test is that the equation is under-identified. As the P-value I obtain is very small (0.0001) I can reject the null hypothesis, which indicates that my model is identified. However, a rejection of the null should be treated with caution, as weak instrument problems are not considered using this test.

The test for weak identification reported by ivreg2 is based on the Cragg-Donald (1993) F statistic, a closely linked to the Anderson canonical correlations statistic. "Weak identification" arises when the excluded instruments are only weakly correlated with endogenous regressors. Stock and Yogo (2005) have compiled critical values for the Cragg-Donald F statistic for several different estimators, which Stata has reported. The F statistic of 9.152 suggests that my model is not weakly identified, but this statistic can only be interpreted provided we are willing to assume homoskedasticity and independence. The Sargan statistic is an over-identification test of all the instruments and the P-value of 0.4431 shows that my model is not over-identified. As the fixed effect results are substantially different from my instrumental variables estimates, this indicates that the model may have been mis-specified to some degree. This is likely to have arisen through the problem of weak instruments already mentioned. It can also be explained in part by selection bias: if parents send their least able children to work then OLS and fixed effects will overestimate the effect that work has on school performance. Hence why the fixed effect coefficient on child labour is negative (but small in magnitude) whereas the IV estimates produce a positive (insignificant) coefficient.

Discussion

Four assumptions are required for OLS estimation techniques to be unbiased: the model must be linear in parameters, there must be random sampling and sample variation in the explanatory variable and the zero conditional mean assumption must hold. It is possible that the model has been misspecified by using a linear model if the relationship between child labour and the educational attainment of the children is not linear. This is quite feasible as low levels of child labour are likely to have little impact on test scores but higher levels may have an increasingly negative impact as the children are becoming too tired to concentrate in school. However as most of the children in Vietnam are only working relatively few hours per day, approximating the relationship to be linear is not a vast misspecification.

The survey was conducted as a random sample of children from all over Vietnam and there is variation in child labour levels, so the second and third assumptions are not problematic. The possibility that the explanatory variable is correlated with the error term is almost always a concern in simple regression analysis with non-experimental

¹⁰ Stata online help

data. Child labour will be correlated with the residual if there is something unaccounted for in my regressions and hence part of the residual which is impacting on the test score results of the children. For example if parents send their less academic children to work more then it would appear that child labour is causing these poor test scores when in fact it is due to sample selection bias. If the omitted factor in the residual is negatively correlated with child labour (for example child ability) then there will be a negative bias on the OLS estimates. This could account for why my OLS regression results show a negative sign whilst the IV estimates do not.

Instrumental variables estimation allows one to interpret the results as causal but the weak instrument problem is a common worry. When the instrument is only weakly correlated with the explanatory variable the variance of the IV estimator can be high – that is the standard errors will be high and so coefficients may be insignificant. This is apparent in my results, as the child labour variable has become insignificant when it was subjected to the instrumental variable approach and the standard error has increased from 0.605 to 4.201. The event variables were the most successful instruments available to me but still did not strongly follow child labour as the magnitudes of their coefficients in the first stage regressions are only 0.404 and 0.431 for events 28 and 29 respectively.

The use of instruments that explain little of the variation in the endogenous explanatory variables can lead to large inconsistencies in the IV estimates even if only a weak relationship exists between the instruments and the error in the structural equation¹¹. Bound, Jaeger and Baker (1995) re-examine the results of a paper by Angrist and Krueger, who used large samples from the US Census to estimate wage equations in which quarter of birth is used as an instrument for educational attainment. They find that, despite huge sample sizes, their IV estimates may still suffer from finite-sample bias and be inconsistent. This indicates that the use of large data sets does not necessarily protect researchers from quantitatively important finite-sample biases. My F statistic for the IV estimation is 25.08 and the R² is 0.284. These values are not much smaller than those obtained for the OLS regression: F statistic of 25.95 and R² of 0.300. Therefore I can conclude that my model is not suffering badly from finite sample bias but the weak instrument problem is likely to remain a major issue. There is no ideal instrument for child labour in the dataset.

Beegle and Dehejia (2004) use panel data from Vietnam and an instrumental variables strategy to evaluate the effect of child labour participation on outcomes over a five-year period. In contrast to my results, they find significant negative impacts of child labour and school participation and educational attainment. However an important difference with their approach is that they are using a panel data set which enables them to capture the effects of child labour over time. The negative impacts of child labour may not be immediately visible but are likely to augment over time.

Another interesting result from their work is that those who worked as children are likely to earn a higher wage as adults. This supports the evidence that the education system in Vietnam is inefficient and ineffective in providing substantial returns to schooling.

¹¹ Bound, Jaeger & Baker (1995)

A subsequent paper written later in 2004 by Beegle and Dehejia in conjunction with Gatti, uses the same panel data set (Vietnam Living Standards Survey) to evaluate the causal effect of child labour participation. They find that children who worked when they were young are significantly less likely to be attending school five years later, indicating that much of the reduction in subsequent school attainment has arisen through this drop in enrolment. Again this is examining the outcomes of child labour in the medium term. However they estimate that from age 30 onward the forgone earnings attributable to lost schooling exceed any earnings gain associated with child labour. This is evidence for the long-term negative consequences of child labour but also implies that reducing the phenomenon will require households to be very forward looking and to have the necessary access to forms of credit.

Conclusion

Child labour is a very high profile issue in today's world particularly as it is believed to have severe negative consequences for human capital accumulation. Although the problem is not very severe in Vietnam, it is traditional for children to contribute to household work and this is considered beneficial for their personal development. But, there are remain a number of children, particularly girls that work outside of agriculture and longer than the legal limits set out in the Labour Code¹². Children in rural areas are much more likely to work, at every age, than are children in urban areas¹³.

The conclusion that I draw from my results is not that child labour is not a concern but that at the relatively low levels experienced by the sampled 12 year-olds in Vietnam, it is not having a significant impact on how they perform at school. However, at such a young age the children are unlikely to have been working for a long time and it is quite feasible that the potential negative impacts of the labour only accrue after several years of work outside of school. As it stands, labour work is not significantly impacting on enrolment: there is little trade-off between classroom hours and work so it is therefore not surprising that it is not negatively impacting on educational attainment. It is feasible that children who engage in child labour may benefit from the work experience. A moderate amount of work in safe conditions can allow children to develop useful skills and a sense of responsibility¹⁴. The child may value their education more if they have to work to afford schooling costs.

My results provide a rationale for why we observe child labour and suggest potentially lower global returns to eliminating child labour than those found in the ILO report¹⁵. Low levels of child labour do not have a negative impact on test scores in the short run. Child labour can play a role as a buffer against transitory shocks in rural areas¹⁶. Reducing child labour will require parents to internalise the long-term positive externalities to the children from reducing child labour and to be able to pay the costs of

¹² Edmonds & Turk (2003)

¹³ Edmonds & Turk (2003)

¹⁴ Edmonds & Turk (2003)

¹⁵ Beegle & Dehejia (2004)

¹⁶ Beegle, Dehejia & Gatti (2006)

schooling without this labour. This conclusion supports one of the main findings of the ILO (2003) report that household-level transfers are required for the voluntary elimination of child labour to occur.

REFERENCES

- Akabayashi, H. and Psacharopoulos, G. (1999). "The Trade-off Between Child Labor and Human Capital: A Tanzanian Case," *Journal of Development Studies*, 35(5): 120-140
- Angrist, J., and A. Kreuger (1991). "Does Compulsory Schooling Attendance Affect Schooling and Earnings?" *Quarterly Journal of Economics*, 106: 979-1014
- Angrist, J., and A. Kreuger (1992). "The Effect of Age at School Entry on Educational Attainment: An Application of Instrumental Variables With Moments From Two Samples," *Journal of the American Statistical Association*, 87: 328-336
- Baland, J., and J. Robinson (2000). "Is Child Labor Inefficient?," *Journal of Political Economy*, 108:663-679
- Basman, R. (1960). "On Finite-Sample Distributions of Generalised Classical Linear Identifiability Test Statistics," *Journal of the American Statistical Association*, 55: 650-659
- Basman, R. (1963) "Remarks Concerning the Application of Exact Finite Sample Distribution Functions of GCL Estimators in Econometric Statistical Inference," *Journal of the American Statistical Association*, 58: 943-976
- Basu, K. (1999). "Child Labor: Cause, Consequence, and Cure with Remarks on International Labor Standards," *Journal of Economic Literature*, 37: 1083-1119
- Basu, K. and Van, P.H. (1998). "The economics of child labour," *American Economic Review*, vol 88(3): 412-27
- Beegle, K., R. Dehejia and R. Gatti (2003). "Child Labor, Crop Shocks and Credit Constraints," NBER Working paper No.10088
- Beegle, K. and R. Dehejia (2004). "The Education, Labour Market and Health Consequences of Child Labor," CEPR Discussion Paper No. 4443
- Beegle, K., R. Dehejia and R. Gatti (2004). "Why Should We Care About Child Labor? The Education, Labor Market, and Health Consequences of Child Labor," NBER Working Paper No.10980

Beegle, K., R. Dehejia and R. Gatti (2006) "Child Labor and agricultural shocks," *Journal of Development Economics* vol 81(1): 80-96

Bound, J., D. Jaeger and R. Baker (1995). "Problems With Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak," *Journal of the American Statistical Association*, vol 90(430): 443-450

Cavalieri, C. (2002). "The Impact of Child Labor on Educational Performance: An Evaluation of Brazil." Manuscript

Chau, Ry and Dam (2000) "Extra Classes and Learning Outcomes of Eight-Year-Old Children in Vietnam" Working Paper No. 29, Young Lives

Cockburn, J. and B. Dostie (2007). "Child Work and Schooling: The Role of Household Asset Profiles and Poverty in Rural Ethiopia," *Journal of African Economies*, vol 16(4): 519-563

Dercon, S. and P. Krishnan (1996). "Income Portfolios in Rural Ethiopia and Tanzania: Choices and Constraints," *Journal of Development Studies* 32(6): 850-75

Edmonds, Eric (2001). "Will Child Labor Decline with Improvements in Living Standards? A Case Study for Vietnam." Dartmouth College Mimeo.

Edmonds, E. and C. Turk (2003). "Child Labor Transition in Vietnam," in P. Glewe, N. Agrawal, and D. Dollar (eds), *Economic Growth, Poverty and Household Welfare: Policy Lessons from Vietnam*. Washington DC: World Bank

Heady, C. (2003). "The Effect of Child Labor on Learning Achievement," *World Development*, 31: 385-398

Jaeger, D.A., and R.M. Baker (1995). "Problems with Instrumental Variable Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak," *Journal of the American Statistical Association*, 90 (430): 443 -450

Harpham, T., N. Huong, T. Long, T. Tuan (2005). "Participatory child poverty assessment in rural Vietnam," *Children & Society* 19(1): 27-41

ILO (1995) Report of the National Workshop on Child Labor in Ethiopia, technical report, Eastern Africa Multidisciplinary Advisory Team (EAMAT, ILO)

ILO (1996a) Child Labour: Targeting the intolerable, Volume Report VI(1), Geneva: ILO. Summarised in ILR96

ILO (1996b) Report on the National Workshop on Child Labor Policy and Action Programme for Ethiopia, technical report, Eastern Africa Multidisciplinary Advisory Team (EAMAT, ILO)

Lan, P. and N. Jones (2007) "Education for All in Vietnam: high enrolment, but problems of quality remain," Young Lives Policy Brief 4 www.younglives.org.uk

Patrinos, H.A., and G. Psacharopoulos (1995). Educational Performance and Child Labor in Paraguay," *International Journal of Educational Development*, 15: 47-60

Patrinos, H.A., and G. Psacharopoulos (1997). "Family Size, Schooling and Child Labor in Peru – An Empirical Analysis," *Journal of Population Economics*, 10: 387-405

Psacharopoulos, G. and H.A. Patrinos (2002). "Returns to Investment in Education: A Further Update," *World Bank Working Paper Series*, No. 2881

Ravallion, M. and Q. Wodon (2000). "Does Child Labor Displace Schooling?" Evidence on Behavioural Responses to an Enrolment Subsidy," *The Economic Journal*, 110: 158-175

Ray, R.(2000). "Child Labor, child schooling, and their interaction with adult labor: empirical evidence from Peru and Pakistan," *World Bank Economic Review*, vol 14(2): 347-67

Ray, R. and G. Lancaster (2003). "Does Child Labour Affect School Attendance and School Performance? Multi Country Evidence on SIMPOC Data," manuscript

Rosati, F. and Z. Tzannatos (2004). "Child Labor in Vietnam" *Pacific Economic Review*

Tuan, T., P. Lan, T. Harpham, N. Huony, T. Thach, B. Tod, T. Dua, N. Ha and K. Attawell (2007) "Young Lives Preliminary Country Report: Vietnam" www.younglives.org.uk

World Bank et al (1999). *Vietnam: Attacking Poverty* Joint report of the Government of Vietnam–Donor-NGO Poverty Working Group. Hanoi: World Bank.

Government of Vietnam – Donor Working Group (2000). *Vietnam: Managing Public Resources Better. Public Expenditure Review 2000*. Hanoi: Vietnam Development Information Centre.

Stata online help manuals

www.younglives.org.uk