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Child labor and schooling: consequences of child work on educational attainment

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Child labor and schooling:
Consequences of child work on educational attainment

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Abstract

This thesis attempts to extend the very small previous research on child labor and school achievement. It also seeks to answer the questions regarding why working as a child, even though it may not compete with time in school, is detrimental to a child's human capital accumulation and income potential as an adult. Acquiring a large base of human capital in school is key to obtaining and maintaining employment as an adult and allows for a movement away from poverty. In fact, however, not many studies have examined the most significant measure of cognitive ability - learning achievement. The results from this study support the results from previous research. Working while in school, even very few hours per day, reduces learning and therefore also cognitive ability. Moreover, the results point at the endogenous relationship between child labor and schooling and suggest that because households make joint decisions in allocating children's time to working and schooling, modeling child labor endogenously generates more truthful indications of the effect of child labor on school performance.

Chapter I. General Introduction

I.I. Introduction

When one thinks of child labor what first comes to mind are pictures of very young children working under inhumane conditions in mines, sweatshops, agricultural activities, on city streets or on garbage dumps. These are types of the worst forms of child labor and must be eradicated. However, many, many more children work in other types of formal or informal labor with less detrimental consequences to children's health and development. Even though these types of activities are not as harmful as the most hazardous types of work, working when young, regardless of under what circumstances, has long term adverse effects on children that get transmitted to adult life. One of the most important reasons why working when young is undesirable is because it impacts children's participation and success in school, crucial for obtaining skills useful in the adult labor market. Thus, although the type of work performed seems harmless in terms of the physical and mental health of the child, it has a very high potential to lead to lowered adult standard of living and increased incidence of poverty.

Most of the previous research in the area of children's work and education have focused on laying out the mechanisms of how working and schooling compete for the child's time. Measures of schooling outcomes such as enrollment, attendance, dropout rates, grade-for-age and promotion have been used to characterize educational success. However, not many studies have examined what policy makers should really be targeting; learning achievement. The reason why academic achievement is the most significant measure of educational outcomes is because this is the only measure that actually captures what the child learns in school and can consequently be used to measure the amount of human capital the child accumulates. Acquiring a large base of human capital in school is key to obtaining and maintaining employment as adult and allows for a movement away from poverty.

This thesis attempts to extend the previously undertaken research on child labor and school achievement and to answer remaining questions regarding why working as a child, even though it may not compete with time in school, is detrimental to a child's human capital accumulation and income potential as an adult.

I.II. Thesis Organization

The thesis is composed of four main chapters, a general introduction and a general conclusion. To ensure the flow of the thesis as a whole, the four papers that make up the main chapters have been slightly modified and reformatted from the originals. Chapter II, the first main study, is a paper co-written by Peter Orazem of Iowa State University and Guilherme Sedlacek of the InterAmerican Development Bank and will be published in *Eradicating Child Labor in Latin America in the 90s: The Promise of Demand Side Interventions*. (Forthcoming). The book is edited by Orazem, Sedlacek and Zafiris Tzannatos of the World Bank and is a World Bank publication. In Chapter II, which serves as a global background on child labor, we attempt to identify the major trends in child labor in the world from 1950 until today and we conclude that most of the variation in the incidence of child labor between countries can be explained by the importance of agriculture to a country's GDP, adult literacy rates and income per capita. This chapter does not discuss the effect of children's work on educational outcomes per se, nonetheless it lays out the most important mechanisms explaining why child labor appear and why different approaches aimed at eradicating child labor in the world have been more or less successful.

Chapter III is written together with Orazem and Mario A. Sánchez of the InterAmerican Development Bank. This paper will also appear in *Eradicating Child Labor in Latin America in the 90s: The Promise of Demand Side Interventions*. (Forthcoming). Focusing on Latin America, we employ a unique data set on 3rd and 4th graders and evaluate the effects of child work on mathematics and language scores. We find that the students who work only some of the time outperform those who work all the time, and those who never work outperform both. The advantage for children who do not work is large while the advantage for occasional child laborers is much smaller. After controlling for child, household, teacher and school characteristics we conclude that time spent working outside the home is the most important predictor of the students' success in school.

The third main chapter of the thesis, Chapter IV, extends the study in Chapter III by using an additional multi-country data set on 7th and 8th graders. While modeling the same relationship between child work and test scores as in Chapter III, Chapter IV uses the instrumental variable approach to allow child work to affect schooling outcomes both as a cause and as a consequence of academic performance. In this study, I explore the differences between treating child work exogenously versus endogenously and discuss the reasoning behind why the relationship between child labor and schooling is not simply one way. My results suggest that treating child labor as exogenous results in a great upward bias in the estimated impact on test scores. The true adverse effect of working while in school is revealed when treating children's work as a function of child specific, parental and household, teacher, school, community and country level variables.

The final major paper of the thesis, Chapter V, is again co-written together with Orazem and was funded by the International Labour Organization and the U.S. Department of Labor. This chapter serves as a guide for future studies in the area of child labor and schooling outcomes and highlights important problems to address when conducting research. Sampling design, variable definition, data collection and estimation technique aspects are discussed. Moreover, continuing the study of child work and test scores, this chapter takes the data on 7^{th} and 8^{th} graders one step further and looks at how the adverse effect on test scores changes as the number of hours worked inside and outside the household increases.

Chapter II. Changing Patterns of Child Labor Around the World Since 1950: The Roles of Poverty, Parental Literacy and Agriculture

A paper published in *Eradicating Child Labor in Latin America in the 90s: The Promise of Demand Side Interventions*. Forthcoming.

Victoria Gunnarsson, Peter F. Orazem and Guilherme Sedlacek

II.I. Introduction

Child labor is widely considered to be a social problem that must be minimized, if not eliminated. The 1989 Convention on the Rights of the Child, which required that children be protected from work that harms the child's health, educational opportunities, and mental, physical, social or moral development, was signed by 191 countries. Despite this widespread condemnation, about one of every eight children aged 10-14 works worldwide.

Nevertheless, there has been progress in lowering the incidence of child labor over the past half-century. To formulate policy to maintain that progress, it is important to take stock of why child labor has decreased in the past. This study explores the roles of declining poverty, improving adult literacy, and economic transformation from a rural agrarian economy to an urban industrialized base. All prove to be important in explaining why child labor has declined over time, why child labor persists, and how it may be combated in the future.

II.II. Factors that Affect Child Labor

Through history, children have worked to contribute to family income. In turn-of-the-century households in the U.S., income derived from child labor was used primarily for immediate household consumption needs (Parsons and Goldin, 1989). Some child labor involved parents who wanted to maximize their own consumption at the expense of their children's future. For example, Galbi (1997) found that child labor substituted for adult labor in the early years of the industrial revolution. Horrell and Humphries (1995) argued that industrialization also caused children to initiate work at younger ages as their older siblings gained independence and therefore left the household. However, the increase in child labor during the early period of the industrial revolution appears to be due more to falling income opportunities for parents. Adults without factory experience proved to be poor factory workers. As the first generation of working children aged and became parents, their children were less likely to work. Therefore, the time path of child labor participation during the industrial revolution appears to be consistent with most contemporary studies that find that the incidence of child labor declines as household income rises.

The preponderance of evidence across many different countries finds that child labor is primarily a result of poverty and not parental indifference to their children's needs. That conclusion is immediately apparent in Figures II.1a and II.1b. The figures show scatterplots of per capita income and the proportion of children aged 14 and under who work for a wide range of countries for the years 1960 and 1990. Several conclusions can be derived from the plots. First, there has been a clear reduction in the incidence of child labor. While in 1960, nearly 28 percent of children were working, the average in 1990 had fallen to less than 15 percent. Worldwide, the decrease in the level of child labor over time corresponds to a decline in the number of countries with very low incomes. Countries such as Burkina Faso, Mali, Niger, and Thailand experienced large reductions in child labor force participation rates as their real incomes rose from absolute poverty levels. Countries that did not experience rising real per capita incomes (Laos, Nicaragua) maintained their high levels of child labor.

A second implication of the scatterplots is a clear negative cross-sectional relationship between a county's income level and its use of child labor. Low-income countries use child labor heavily while high-income countries use child labor little if at all. The cross-sectional relationship is convex, so at first, child labor declines rapidly as per capita income rises. However, as per capita income continues to increase beyond $1000 (in 1999 prices), additional decreases in child labor participation rates become more modest. In addition, while some countries have eliminated child labor with per capita incomes as low as $1000, there are other countries with per capita income levels well above $1000 that still have above average child labor rates.

The general pattern of declining child labor force participation rates with rising per capita incomes, both across time periods and across countries, have led some observers to suggest that income growth will correct the child labor problem by itself. However, while changes in income are negatively correlated with changes in child labor participation rates, the correlation is only -0.26. Moreover, the persistence of child labor in some of the countries well beyond the $1000 income threshold also suggests that raising income alone may not be enough to eradicate child labor. Child labor may still persist if there are other factors that raise the value of child time in the labor market, or if there are low perceived returns to alternative uses of child time, particularly in school.

Several studies have shown that child time allocation responds to the strength of the local labor market for children. Levy (1985); Rosenzweig and Evenson (1977); and King, Orazem and Paterno (1999) found that as local market wages or demand conditions for children rise, the probability of child labor rises. By far the heaviest user of child labor is agriculture. Ashagrie (1997) estimates that 70 percent of working children are engaged in agricultural activities. The next heaviest users of child labor have much smaller shares, including manufacturing (8.3%), trade (8.3%) and personal services (6.5%). This suggests that the importance of agriculture in the economy can be used as a proxy for the relative strength of child labor demand in the country.

Child labor and education are alternative uses of time. While most working children are also enrolled in school, evidence suggests that working children have less academic success and complete fewer years of school. Consequently, factors which make schooling more productive may cause child labor to decline. Most empirical investigations of the factors influencing whether parents send their children to school find that, other things equal, parental education has a strong positive impact on their children's schooling (Rosenzweig and Wolpin, 1994; Grootaert and Patrinos, 1999). More educated parents can increase the productivity of their child's time in school - whether by reinforcing what is learned in school, helping with homework, or valuing their children's efforts in school. Many studies have found that mother's education is particularly important for their children's schooling success (World Bank, 2001), but often father's education has proven important as well. Regardless of the specific mechanism, we would anticipate that improvements in adult literacy would increase child time in school and thus lower the incidence and intensity of child labor.

II.III. Stylized Facts Regarding Child Labor

The previous discussion suggests that we should be able to explain the incidence of child labor in a country by the country's income level, its industry mix, and its adult literacy rate. While past analysis has concentrated on household-level data sets, similar arguments can justify an attempt to explain the variation in child labor participation rates across countries.

II.III.I Data

The International Labour Organization has generated estimates of the employment rates for children aged 10 to 14 by country since 1950. The data are reported in the 1995 *Bulletin of Labour Statistics.* The data are based on survey questionnaires, International Labour Organization (ILO) internal data, and on data computed from ILO estimates and projections.[1] Information is available for up to 201 countries per decade from 1950 through 1990.[2] Summary information on child labor participation rates by year and continent are reported in Table II.1.

The incidence of child labor has declined steadily since 1950 worldwide. It has been virtually eliminated in the wealthiest economies of Europe and North America, but these countries already had low levels of child labor in 1950. The biggest improvement over the period was in Asia where the proportion of children working declined 20 percentage points. The incidence of child labor declined about ten percentage points in Africa, which nevertheless still retains the World's highest current rates of child labor. Child labor declined by eight percentage points in Latin America, but still exceeded 11 percent as of 1990.

The incidence of child labor by continent appears to be inversely related to levels of income. The Penn World Tables report estimates of per capita real income (using a chain-weighted deflator denominated in 1985 US Dollars) for many of these countries from 1950 through 1990. Population weighted indices by continent are reported in Table II.2. World per capita real income rose very slowly between 1950 and 1980 before making some rapid gains in the decade of the 1980s. However, those gains were limited to the countries of Asia and the industrialized west. Latin America experienced some rapid gains in per capita real income before 1980, but those gains reversed after 1980. The slowest income gains were in Africa where child labor incidence is the greatest. The simple correlation between per capita income level and child labor across countries is -0.82, suggesting a strong inverse relationship between a country's poverty level and its incidence of working children.

Statistics on child labor by industry imply that countries relying most heavily on agriculture should have the highest demand for child labor. We use the World Bank's estimates of agriculture's share of total GDP by country to index this source of potential demand for child labor in the country. While agriculture's importance in the economy varies considerably across continents, it has fallen less than one percentage point overall. Modest reductions in Latin America and Asia should have contributed to declining child labor, but there has been also no change in the importance of agriculture in Africa. The simple correlation between agriculture's share of GDP and child labor is 0.78, so there is strong evidence that agrarian countries use children's labor services more intensively.

Over the same period, the World Bank reports the share of the adult population (aged 25 years or over) that is considered functionally illiterate. This is used as a measure of parental education. More educated parents are believed to have stronger taste for schooling and to make child time in school more productive. Between 1970 and 1990, the proportion of the world's adult population that was illiterate fell nearly 14 percentage points. Reductions in adult illiteracy of nearly 20 percentage points were experienced in Africa and Asia. Illiteracy in Latin America fell almost 12 percentage points. Consequently, improving education levels of parents would be expected to be a positive factor for their children's schooling. Children who spend more time in school would be expected to spend less time at work. Consistent with that conjecture, the simple correlation between the level of adult illiteracy and the incidence of child labor is 0.78.

II.III.II Regression Analysis and Simulation Outcomes: World

Simple correlations support the conjecture that child labor is strongly influenced by a country's level of income, adult literacy and reliance on agriculture. To evaluate the relative importance of these factors, we formulate a regression model of the form:

$$CL_{it} = \alpha + \beta_1 \ln(Y_{it}) + \beta_2 [\ln(Y_{it})]^2 + \beta_3 Agshare_{it} + \beta_4 Illiteracy_{it} + \Sigma D_t + e_{it} \quad \text{(II.I)}$$

where CL_{it} is the percentage of children aged 10-14 in country i and year t who are working; $ln(Y_{it})$ is natural logarithm of real per capita GDP; $Agshare_{it}$ is the agriculture's share of GDP; $Illiteracy_{it}$ is the adult illiteracy rate; D_t is a vector of yearly dummy variables which control for world-wide time-specific changes in the demand for child labor which could be due to international efforts to combat child labor or to encourage child schooling; and e_{it} is a random error term. The logarithmic form of per capita GDP proved to fit better than the linear form. The quadratic specification in $[ln(Y_{it})]$ also proved most consistent with the data. The quadratic specification could not be rejected, but higher order terms proved unnecessary.

The regression results are reported in Table II.3. For the full period, we could only include the quadratic terms in *[ln(Y_{it})]* because the information on *Agshare* and *Illiteracy* was not available. The full specification could be estimated only over the 1970-1990 period.

The estimates are remarkably stable over time. In fact, the null hypothesis that the coefficients on per capita income are the same for all years could be only weakly rejected over the 1950-1990 period and could not be rejected over the 1970-1990 period.[3] Figure II.2 traces out the estimated relationship between per capita income and child labor allowing variation in the coefficients and constant terms over time. The shape of the relationship hardly varies. One implication of Figure II.2 is that falling child labor worldwide has been accomplished by movement down this stable curve. As real incomes have improved worldwide, fewer children have had to work.[4]

The convex shape of the relationship has another implication. As per capita income increases, progressively larger increases in per capita income are necessary to lower child labor by another percentage point. As a consequence, the poorest countries can experience rapid reductions in child labor if they can raise their income levels. In Figure II.2, for example, a country that is at the lowest quartile per capita income level will experience a decrease of child labor of about 1.4 percentage points for every $100 increase in per capita income. In contrast, a country at the median level of per capita income worldwide will experience a 0.5 percentage point decrease in child labor for every $100 increase in per capita income. In other words, planners can concentrate on fostering economic development and income growth in the poorest countries and expect child labor to fall in response. However, child labor becomes less sensitive to further increases in average income. Hence, planners cannot expect to eradicate child labor solely on the strength of further increases in income.

The regression analysis is repeated over the more recent time frame for which we have access to information on *Agshare* and *Illiteracy*. The conclusions from the regression in the first column of Table II.3 stand up in column two. The test of the null hypothesis that the impact of changes in per capita income on child labor is constant over time could not be rejected at standard significance levels. As before, the conclusion is that reductions in child labor follow the progress of the country's path of income growth, but that the relationship flattens out as the country's per capita income rises above the median. In addition, as a country's *Agshare* and *Illiteracy* increases[5], child labor increases significantly. A ten percent increase in agriculture's share of GDP increases child labor by about 20 percent. A ten percent increase in adult illiteracy also raises child labor by 20 percent. The implication is that increasing adult literacy and/or developing the nonagricultural sector of the economy will lower the incidence of child labor, even if child labor is no longer sensitive to income growth.

The pattern of coefficients on the year dummies suggests that until the last decade, child labor was actually trending upward worldwide. Absent improvement in per capita income and adult literacy, pervasive trends in child labor would have led to higher child labor force participation by the end of the period than in 1950.

These simple models appear to do a reasonable job of capturing the time series and cross sectional variation in child labor. The quadratic relationship in per capita income explained 67 percent of the variation in child labor across countries from 1950 to 1990. After adding agricultural intensity and illiteracy, the model explained 80 percent of the variation in child labor across countries between 1970 and 1990. The parameter estimates allow us to measure how much of the change in child labor can be attributed to changes in the levels of per capita income, agriculture and illiteracy over time, using the formula $\beta_j\, dX_{jt}/dt$. This is directly estimable as the change in the sample mean of the variable over the sample period multiplied by its respective coefficient.[6] The estimates are reported in Table II.3. They suggest that over the 1950-1990 period, virtually all of the seven percentage point reduction in child labor participation worldwide can be attributed to increases in per capita income. When the fuller specification is employed over the shorter sample period, increases in per capita income are still shown to explain roughly seven percentage points reduction in the incidence of child labor. Reductions in adult illiteracy also lowered the incidence of child labor by about 2.5 percentage points. *Agshare* explained almost none of the change in child labor over time because the level of *Agshare* did not change much over the period.

II.III.III Regression Analysis and Simulation Outcomes: Latin America

Using the worldwide regressions as a frame of reference, a similar regression methodology was employed over the sample of countries from South America, Central America and the Caribbean. The implications of that analysis are similar to those based on the world sample, although the magnitude of the effects are different in Latin America. Over the full 1950-1990 time period, increases in real per capita income significantly reduced the child labor force participation rate in Latin America. Evaluated at changes in sample means over the 1950-1990 period, increases in real per capita incomes lowered the child labor participation rate by 2.9 percentage points or roughly 40 percent of the total change. This is smaller than the seven percentage point drop in child labor that could be attributed to improvements in per capita income worldwide. The reason is that per capita incomes in Latin America were already at or above the median per capita income in the world, placing those countries in the flatter portion of the relationship between child labor and income shown in Figure II.2.

This conclusion is reinforced in the fourth column over the sample period where per capita incomes in Latin America had further risen relative to world averages. From 1970 to 1990, changes in real per capita income had no effect on average child labor participation in Latin America. However, improvement in adult literacy and reductions in agriculture's share of production had strong negative effects on child labor. The reduction in adult illiteracy is responsible for a 4.2 percentage point reduction in child labor participation compared to the 2.5 percentage point effect worldwide. Reductions in agriculture's share of production lowered child labor by an additional 1.2 percentage points compared to the negligible effect worldwide.

It is important to emphasize that the negligible impact of improvements in average per capita income on child labor in Latin America over the 1970-1990 period does not imply that income is unimportant. In fact, holding average income constant, higher levels of illiteracy and agricultural production suggest a more unequal income distribution. Consequently, the large effects of these variables on child labor may be due to a larger share of low-income households within the country. Therefore, while general increases in average income levels in the country may not affect child labor, policies which raise incomes at the lower end of the distribution might still have some effect. However, even at the upper end of the income distribution in these countries, child labor is still practiced. Consequently, income transfer programs alone will not eliminate child labor in Latin America.

II.IV. Conclusion

The preponderance of evidence suggests that child labor is strongly tied to the level of household incomes. In fact, increases in per capita incomes can explain almost all of the reductions in child labor worldwide since 1950. However, child labor becomes less responsive to additional increases in per capita income as the level of per capita income rises. In Latin America, where average per capita income exceeds the world median level, additional increases in average income may not have much effect.

While transferring income from the rich to the poor in these countries may lower the incidence of child labor to some extent, such programs cannot eliminate child labor. Even an improbably ambitious tax and income transfer program that transferred income from the wealthiest families to the lowest income quintile households sufficiently to bring all households to the level of the second income quintile would not raise income sufficiently to eliminate child labor. Of course, the increased taxation of the highest income quintile households would presumably induce some labor market entry from children in the formerly wealthier households.

The sensitivity of child labor participation rates to adult literacy rates and the share of agriculture in total production suggest other avenues by which policy could reduce child labor. Policies which lower the value of child time at work, or alternatively, which raise the value of child time in school or other non-labor activities may have a significant impact on the incidence of child labor. Policies which induce illiterate parents to value literacy in their children may also be effective.

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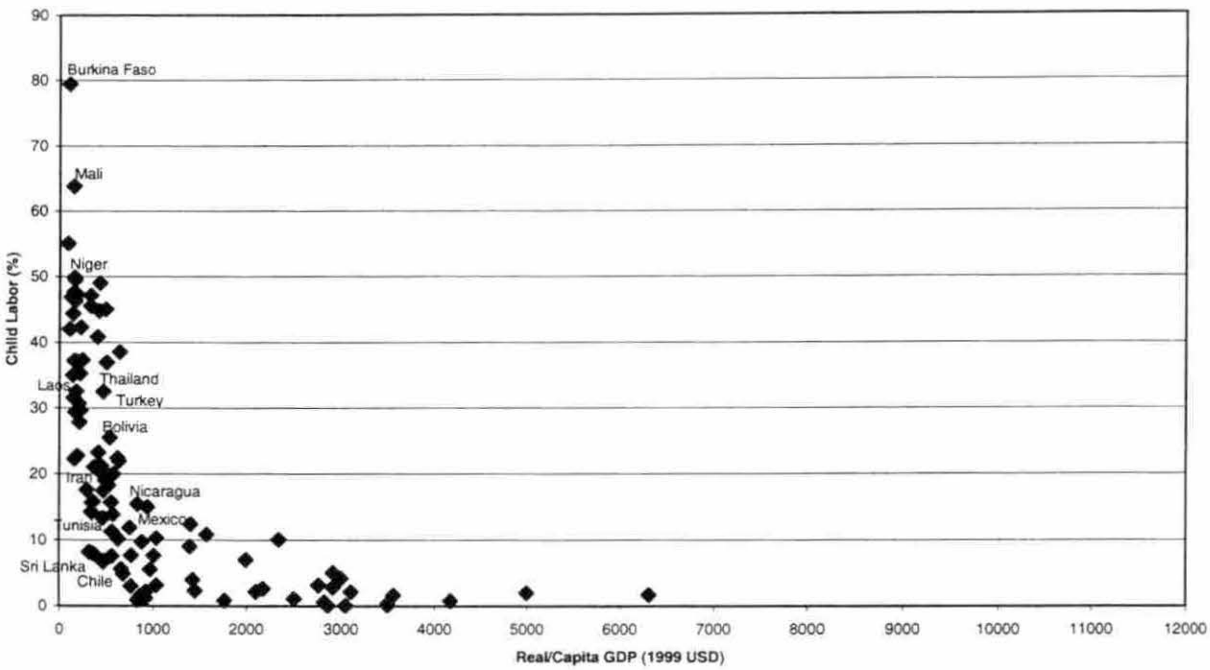

Figure II.1a Real Per Capita GDP and Child Labor, 1960.

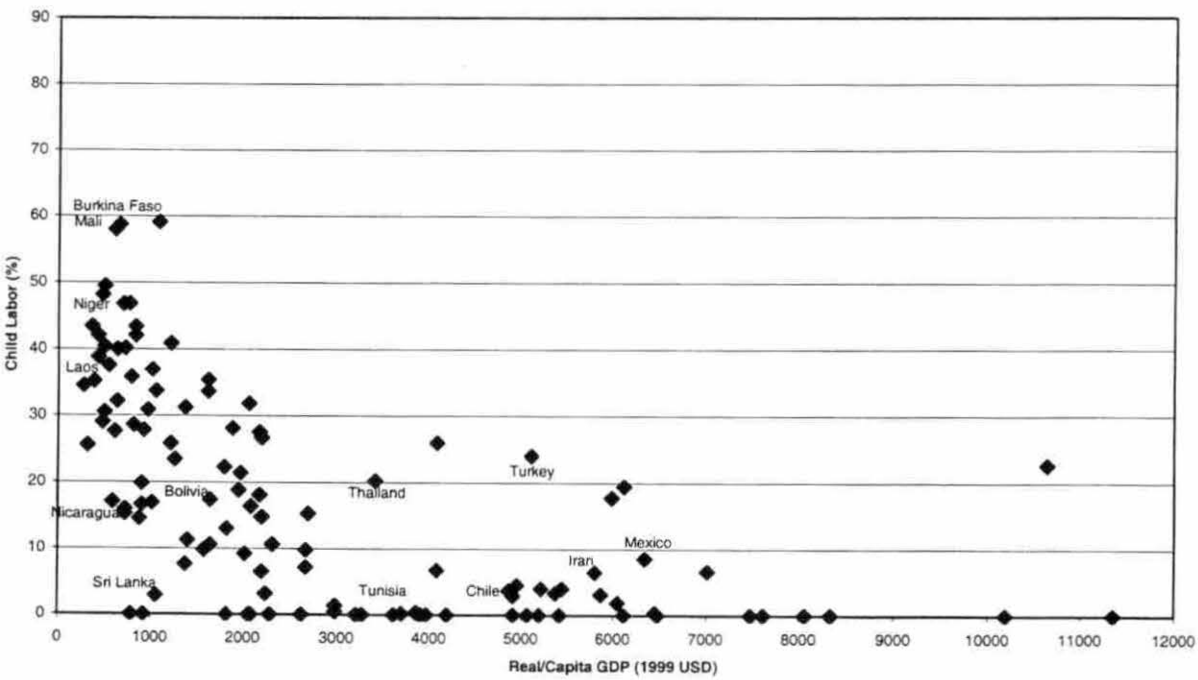

Figure II.1b Real Per Capita GDP and Child Labor, 1990.

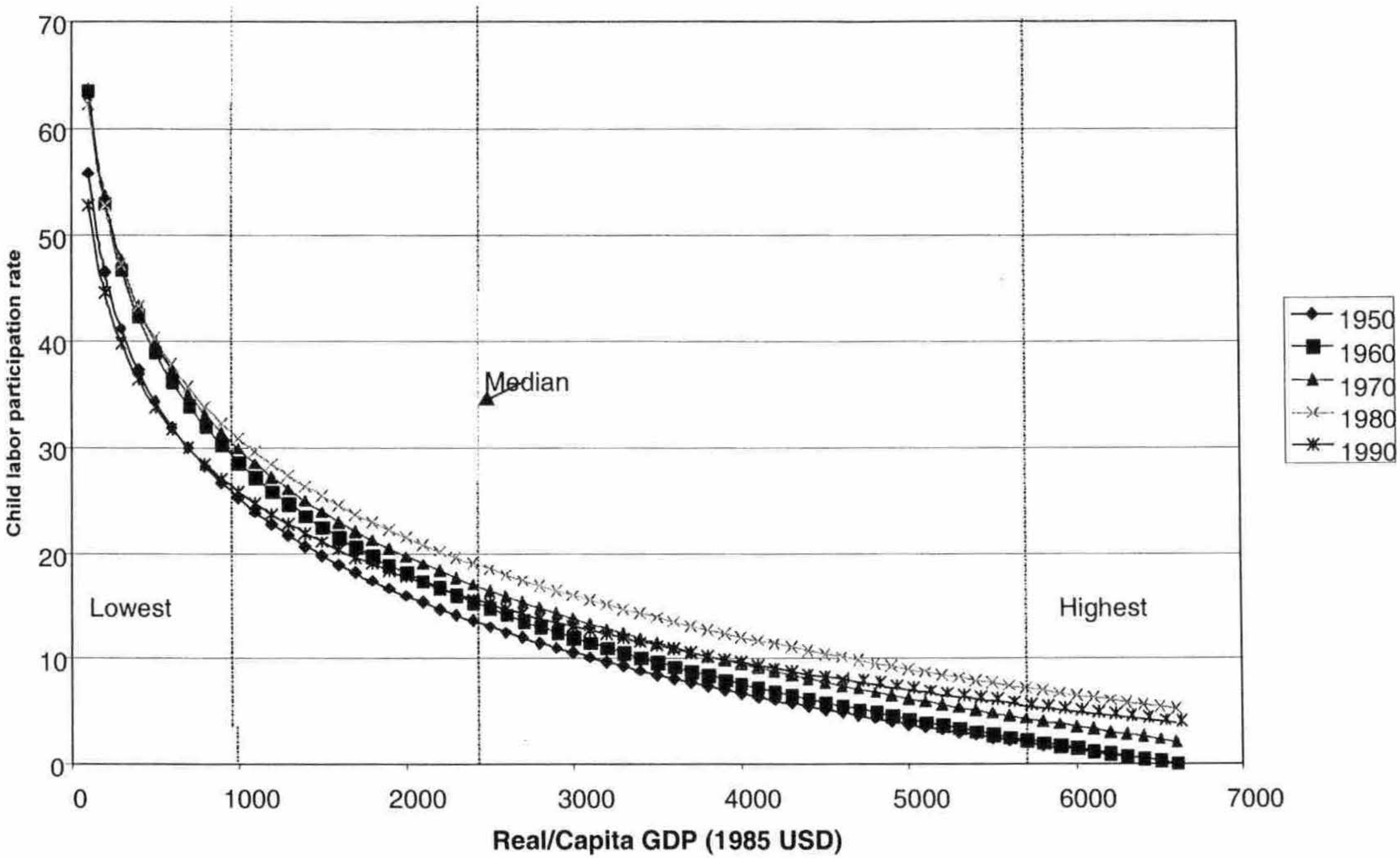

Figure II.2 Child Labor vs. Real Per Capita GDP 1950-1990. Based on the Estimates Reported in Column 1 of Table II.3.

Table II.1 Population Weighted Child Labor Participation by Continent (%).

Continent	1950	1960	1970	1980	1990
World	27.6	24.8	22.3	19.9	14.7
Africa	38.4	35.9	33.1	31.0	27.9
Asia	36.1	32.3	28.4	23.4	15.2
Latin America & Caribbean	19.4	16.5	14.6	12.6	11.2
North America, Western Europe and Australia	6.1	3.8	2.1	0.5	0.1

Sources: ILO (1996) and authors calculations based on Bulletin of Labour Statistics, 1995 I-IV, ILO and Penn World Tables.

Table II.2 Population Weighted Per Capita GDP, Agricultural Share of GDP and Illiteracy, by Year and Continent.

Continent	1950	1960	1970	1980	1990
World					
Per capita GDP[a]	2559	2225	2974	2968	4023
Agriculture Share[b]			9.5	11.0	8.7
Illiteracy[c]			41.1	36.1	27.3
Africa					
Per capita GDP[a]		824	1050	1417	1449
Agriculture Share[b]			23.1	18.9	20.9
Illiteracy[c]			67.9	57.6	46.8
Asia					
Per capita GDP[a]		876	1286	1698	2192
Agriculture Share[b]			24.6	19.1	17.9
Illiteracy[c]			51.2	41.4	32.8
Latin America & Caribbean					
Per capita GDP[a]	1981	2340	3215	4541	4132
Agriculture Share[b]			12.8	10.1	7.2
Illiteracy[c]			27.2	21.1	15.3
North America, Western Europe and Australia					
Per capita GDP[a]	5506	7141	10132	10953	13756
Agriculture Share[b]			1.3	2.7	1.4
Illiteracy[c]			1.3	1.7	0.7

[a] Author's calculations based on GDP per capita in 1985 US dollars. *Source:* Penn World Tables. [b] Author's calculations based on Agricultural share of GDP. *Source:* World Bank and Penn World Tables. [c] Author's calculations based on Adult Illiteracy rates computed by the World Bank.

Table II.3 Regression Analysis of Child Labor Force Participation Rates by Country, 1950-1990.

	World Sample		Latin America Sample	
Variable	**1950-1990**	**1970-1990**	**1950-1990**	**1970-1990**
ln Y	-59.851*	-63.902*	-8.480*	-0.076
	(6.005)	(7.835)	(1.281)	(2.174)
$(\ln Y)^2$	2.971*	3.546*		
	(0.385)	(0.476)		
Agshare		0.182*		0.211
		(0.054)		(0.107)
Illiteracy		0.178*		0.345*
		(0.027)		(0.064)
D_{50}	-1.473		5.721*	
	(1.649)		(2.499)	
D_{60}	0.616		1.371	
	(1.369)		(2.334)	
D_{70}	1.957	-0.389	2.595	-1.090
	(1.333)	(0.027)	(2.261)	(0.762)
D_{80}	3.165*	2.217	2.801	0.070
	(1.306)	(1.149)	(2.236)	(1.726)
Constant	298.236*	285.556*	75.441*	-0.204
	(23.102)	(32.583)	(10.327)	(18.882)
R^2	0.672	0.798	0.365	0.565
N	547	285	122	63
Observed Change in CLFP[a]	-7.051	-8.653	-6.832	-0.951
$\beta_i(dX_{it}/d_t)$[b]				
ln Y	-7.110	-7.222	-2.893	-0.013
Agshare		-0.152		-1.171
Illiteracy		-2.493		-4.171
$\sum_i \beta_i(dX_{it}/d_t)$[c]	-7.110	-9.867	-2.893	-5.355

* indicates significance at the 0.05 level. [a] Change in population-weighted child labor force participation rate. [b] Change in population-weighted mean of the regressor times its respective coefficient. [c] Sum of all changes in child labor attributable to changes in weighted sample means of real per capita income, agriculture share and adult illiteracy rate. Standard errors in parentheses.

Endnotes

[1] See Ashagrie *Statistics on Child Labor: A Brief Report,* 1993 for details on these estimates.
[2] Information on some countries is spotty, especially for 1950 and 1960.
[3] The F-statistic is 2.23 which exceeds the critical value at the 0.05 level but not at the 0.01 level. The test of stability over the specification including *Agshare* and *Illiteracy* could only be conducted over the data since 1970. There, the F-test of the null hypothesis of stable coefficients over time could not be rejected. The F-statistic of 1.37 was well below the critical value of 1.98 at the 0.05 level of significance.
[4] Although developed countries have very low incidence of child labor, this was not the case earlier in their histories when their per capita incomes were more similar to those of developing countries today. For example, in 1910, the labor force participation rate for boys aged 10-13 in the United States was 17%, and it was more than 40 percent in the states of the Deep South. Over 72% of the working children were employed in agriculture. Interestingly, per capita incomes at the time in the United States would be equivalent to that of countries at the 25^{th} percentile of per capita incomes today, much higher than per capita incomes in most of the developing world.
[5] The share of agriculture in the economy may also be a proxy for the distribution of income. As a rule, agricultural households lag urban households in average income, just as more agrarian countries lag industrialized countries in average income. Poverty rates in rural areas exceed those in urban areas. Consequently, holding per capita income constant, the variance of per capita income would be expected to increase as agriculture's share increases. Consistent with this presumption, measures of income inequality are typically larger in developing than in developed countries
[6] For the estimated impact of changes in per capita income on child labor, the formula is $\beta_1\{ln\,(Y_{it}) - ln\,(Y_{it-1})\} + \beta_2\,\{[ln\,(Y_{it})]^2 - [ln\,(Y_{it-1})]^2\}$.

Chapter III. The Effect of Child Labor on Mathematics and Language Achievement in Latin America

A paper published in *Eradicating Child Labor in Latin America in the 90s: The Promise of Demand Side Interventions*. Forthcoming.

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III.I. Introduction

Previous work by Neri et al.(2003) and Ilahi et al. (2003) has shown that working as a child is associated with lower wages and higher incidence of poverty as an adult. Because wages rise with years of education, it is clear that if child labor reduces years of schooling completed, adult wages will be reduced. Numerous studies have linked child labor with lower grade attainment. However, the study by Ilahi et al. (2003) also found that child labor lowers the rate of return per year of education. That finding suggests that child labor lowers the amount of human capital produced per grade completed. While plausible, the link between child labor and student achievement in primary schools is not well understood.

There are surprisingly few studies that have examined how child labor affects schooling outcomes. The studies that do examine how work affects performance in school have tended to concentrate on students at the secondary or tertiary school levels. Ehrenberg and Sherman (1987) found that working while in college had little impact on grade point average (GPA). However, working while in school did lengthen the time to graduate and increased the probability of dropout. Research performed at the secondary school level presents a similarly mixed message. D'Amico (1984) found that working while in high school lowered study time but had no impact on class rank. Lillydahl (1990) found that part-time work actually increased GPA when the job involved less than 13.5 hours per week, although the effect dissipated thereafter. Both D'Amico and Lillydahl found evidence that part-time work improved knowledge of business and economics. Others have found evidence that working longer hours harms academic achievement. Howard (1998) found that A-level grades in England declined when the student worked over 15 hours per week, and Singh (1998) reported that as hours worked increased, there was a modest decrease in achievement test scores in the United States.

The general conclusion from these studies is that there is little evidence that working while in school harms school achievement provided that the part-time job does not involve too many hours. In fact, part-time jobs can actually enhance learning in subjects that are complementary with work. Where part-time work harms academic achievement, the effect is small. However, it is dangerous to extend these conclusions derived from studies of high school or college students in developed countries to the case of young children working in developing countries. Part-time work may be more disruptive for attaining basic literacy and numeracy than it is of learning at higher levels. The types of jobs performed by older students in developed countries may also be more complementary with schooling than the low-skilled, manual work performed by young children in developing countries. Older children may also be more able to absorb the physical demands of combining school and work, whereas younger children may find that child labor leaves them too tired to keep up with school.

To our knowledge, there have been no studies of the effects of child labor on student achievement at the primary level. However, policies designed to limit child labor are predicated, at least in part, on the presumption that part-time work reduces the probability that a child will attain literacy and numeracy. On the other hand, some researchers have pointed to the high enrollment rates of child workers as evidence that part-time work and schooling are compatible, presuming that time in school equates with learning regardless of how time is spent out of school.

Using a unique data set on language and mathematics test scores for 3^{rd} and 4^{th} graders in 11 different Latin American countries, this study represents a first attempt to determine which of these presumptions about the effect of child labor on achievement is true, or if both presumptions hold in some locations but not others. The findings are amazingly consistent across countries. In every country, child labor lowers performance on tests of language and mathematics proficiency, even when controlling for school and household attributes. The magnitude of the effect is similar to the percentage reduction in adult wages from child labor reported by Ilahi et al. (2003). The adverse impact of child labor on test performance is larger when children work regularly rather than occasionally. There is only a small advantage in test scores from occasional work versus regular work, so even modest levels of child labor at early ages causes adverse consequences for the development of cognitive abilities. These findings strongly refute the presumptions that child labor may be complementary or neutral with respect to academic performance, provided that the child remains enrolled in school. Instead, child labor consistently makes a year of education less productive in the generation of human capital.

III.II. Methodology

There is a large literature evaluating the factors that affect how children perform in school. Following Hanushek (1986) and Glewwe (2002), the standard methodology is to relate measures of a student's academic performance, Q, to the attributes of the student's household, H, the student's teacher, T, and the student's school, S, and a measure of the student's innate ability, I. To this, we add a measure of the student's time in the labor market, M. The production process can be written

$$Q = f(H, T, S, I, M) \tag{III.1}$$

In practice, family attributes are more important in explaining variation in student achievement in both developed and developing countries. Measures of either the mother's or the father's education and of the income or wealth of the household are typically important in improving the schooling outcomes of their children. Of the school inputs, teacher attributes (teacher education and or experience) appear to be most important in affecting achievement in developing countries (Hanushek, 1995).[1] Class size does not matter in either developing or developed countries. Other school attributes often have mixed or insignificant effects in developed countries, but school attributes appear to be more important in developing countries. The quality of school facilities, access to textbooks, and expenditure per pupil all consistently have positive effects on student achievement (Hanushek, 1995; Kremer, 1995).

Estimates of educational production functions are subject to numerous biases.[2] Among the most common is the lack of adequate control for the student's innate ability. Many studies have attempted to correct for the problem by using two measures of the output measure, Q. If ability has an additive effect on school achievement, the difference between the two output measures will be purged of the ability effect. However, as Glewwe (2002) argues, if measures of H, T, and S only vary slowly over time, the value of the first-differenced measure of achievement is minimal. In addition, if there is considerable measurement error in estimates of Q, the level of Q may be measured more reliably than the change in Q.

Less commonly discussed is the lack of measures on the intensity of time or effort spent in school on the part of the child. This is undoubtedly because of the unavailability of data sets that has measures of the proportion of child time spent in school or at work. As past research suggests that child labor could increase or decrease the productive efficiency of time in secondary or tertiary levels of schooling, and without prior studies for the effect of child labor on productive efficiency at the primary level, we do not make a priori predictions on how child labor will affect achievement of young children.

III.III. Data

In 1997, the Latin-American Laboratory of Quality of Education (LLECE) carried out the First Comparative International Study on Language, Mathematics and Associated Factors for 3rd and 4th graders in Latin America. LLECE collected data initially in 13 countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Honduras, Mexico, Paraguay, Peru, Dominican Republic and Venezuela. Costa Rica's data did not satisfy LLECE's technical requirements for consistency and so they dropped it from the study. As we will see, missing data on child labor in Cuba will cause us to drop it from the analysis as well.
The data set is composed of a stratified sample designed to insure sufficient observations of public, private, rural (communities with < 2,500 inhabitants), urban (between 2,500 and 1 million inhabitants), and metropolitan (> 1 million inhabitants) students in each country. The plan called for data to be obtained from 100 schools in each country with 40 children per school for a total of 4,000 observations per country. Half of the students were to be in the 3rd grade and half in the 4th grade. The stratified samples were designed to be roughly proportional to the populations of five strata, metropolitan public schools, metropolitan private schools, urban public schools, urban private schools, and rural schools. The

administrative criterion deals with the type of direction of the school and differentiates between public and private schools. This distinction was only done for schools in metropolitan and urban areas. The data are divided into two slightly different sets, one for mathematics scores and one for language scores. Because the grades tested were grades three and four, the age of the tested children have a mean of around 9-10 years old.

For budgetary reasons, LLECE had to use a priori geographic exclusions to limit the transportation and time costs of data collection. Exclusion criteria varied from country to country, with common criteria being the exclusion of very small schools, and schools in remote, difficult to access, or sparsely inhabited regions. Because of the cost of translating exams, schools with bilingual or indigenous language instruction were also commonly excluded.[3]

Survey instruments consisted of learning tests on language and mathematics applied to the sample of children of the sampled schools, and self-applied questionnaires to school principals, to the teachers and parents (or legal guardians) of the tested children, and to the children themselves. In addition, surveyors collected information on the socioeconomic characteristics of the community.

Within each school, the choice of which children to survey and test depended on the number of classes. If there were fewer than five classes of fourth and fifth graders, they selected randomly 20 3rd graders and 20 4th graders from all 3rd and 4th graders in the school. If there were five or more 3rd and 4th grade classes, they first picked which four classes to survey, and then picked 20 3rd grade and 20 4th grade students randomly from the children in those classes.

III.IV. An Overview of the Twelve Countries

Tests on language (in Spanish except for Brazil which was in Portuguese) and on mathematics were given to children in the 3rd and 4th grades of selected schools in each of the twelve countries. Table III.1 presents the average test scores for the two exams by country, along with some representative information on each country sample. The language score has a maximum of 19. The average score across all countries is 12, or 63 percent. Country averages vary from a low of 9.8 in Honduras to a high of 17.1 in Cuba. Cuba also dominates the mathematics results with an average score of 26.7, over 53 percent higher than the next highest country. The academic performance in Cuba is truly remarkable, given it has the lowest per capita GDP of the 12 countries.[4]

Unfortunately, while the Cuban test scores appear to be an accurate portrayal of the cognitive abilities of Cuban students, the rest of the data appeared unreliable. Only four percent of the Cuban villages were characterized as poor or very poor, out of line with even the most optimistic characterizations of the Cuban economy. More importantly for our purposes, 94 precent of the Cuban children did not answer the question regarding child labor, so we cannot incorporate the Cuba data into the study. Nevertheless, for researchers interested in devising policies to improve school efficiency in poor countries, it would be useful to study the Cuban case to determine how they generate such superior outcomes.

Turning to the other countries, just less than one-third of the children come from rural areas. Just over one-fifth attend private school. About one-third reside in communities characterized as either low-income or impoverished. Even these simple statistics reveal some interesting patterns. Of eight countries with above average levels of child labor, six have below average scores on both exams, and another (Mexico) scores below average on language but not on mathematics. Only students in Chile score in the upper half on both exams despite above average incidence of child labor. All countries with above average levels of rural population have below average test score except for Mexico. The link between poverty and test scores is less apparent. Of six countries with higher than average poverty incidence, two (Brazil and Chile) score above average on both exams. There is no particular correspondence between the proportion of students in private schools and average test scores.

Table III.2 presents the unconditional estimates of the mean test scores for language and mathematics by intensity of child labor. Children were asked when not in school, whether they worked outside the home often, occasionally or almost never. The answers to these questions create three child labor groups for each country. The test of the difference in means is between those who often work outside the home and those who sometimes or almost never work.

Across 11 countries and two achievement tests, 22 cases in all, the pattern never varies. Those who work only some of the time outperform those who often work, and those who almost never work outperform both. The advantage for children who do not work is large, averaging 27.5 percent for languages and 25.0 percent for mathematics over those who work often. The advantage for occasional child laborers is much smaller, averaging 8.8 percent in languages and 8.1 percent in mathematics. The large gap between children who almost never work and those who work occasionally suggests that there is a significant opportunity cost in the form of lost cognitive skills when young children work just part of the time.

III.V. Regression Analysis

The pattern of unconditional means could be related to other factors that jointly raise child labor and lower test scores. Likely factors which could lead to such outcomes would be poor schools, inadequate teachers, and illiterate parents, all of which would lower expected school productivity and increase incentives to allocate child time to the labor market.

To investigate this, we added available information on school, teacher and household attributes. Because the information was not available for all children, we lose about 50 percent of the sample for which we had child labor information. The biggest cause for missing observations was incomplete data on the parents. We should note that none of the qualitative results we report were sensitive to the inclusion or exclusion of individual regressors in the model, so the results are not driven by this particular choice of variables.

The summary statistics for the observations included in the regressions are reported in Table III.3. Measures of the school include location (rural versus urban), ownership status (public versus private), whether the school is arranged in single grade or multigrade classrooms, and the number of pupils per classroom. Information on the child's teacher is also included. A survey of teachers elicited information on their education and years of teaching experience. Efforts were also made to obtain information on the child's parents through a household survey. This proved expensive and surveyors did not have time to locate parents who were not present at the time of enumeration. Missing information on parents costs about 10,000 observations or one-quarter of the sample for which we have child labor information. The problems of missing observations are most severe in Honduras, Paraguay, Venezuela, and to a lesser extent, Brazil. Because our results are so consistent across countries with varying levels of missing observations, it does not appear that nonresponse bias is driving the results.

The regressions across the 11 countries (excluding Cuba) are reported in Table III.4. The model explains about one-fifth of the variation in test scores across children. Because country dummy variables are included, we can conclude that most of the variation in student cognitive abilities are within countries and not between countries.

The results mimic those commonly found in developing countries (Hanushek, 1995). Urban schools outperform rural schools and private schools outperform public schools. Pupil-teacher ratios have no effect, a common finding. Multigrade classrooms outperform single grade classrooms, although the effect is small: only one to two percent of the mean test score.

In individual country regressions, the conclusions are similar. Government schools never outperform private schools, although they do equally well in some countries. Rural schools never outperform urban schools in language tests, although they do have an advantage in mathematics in three countries. Pupil-teacher ratios and single grade classrooms have small effects of mixed signs.

Teacher education and experience do not have significant effects in Table III.4, contrary to Hanushek's summary of what has been found in developing countries in general but consistent with results in the United States. There is some evidence that teacher education raises student achievement in some countries, but the effect is negligible in most. Teacher experience had mixed effects.

Household factors had strong effects on student outcomes. Having two parents raises mathematics and langauage scores by two to three percent. The average education of the parents or legal guardians has a positive effect that increases in magnitude as education increases. A household with parental education equal to the sample mean raises test scores for his children by five percent in mathematics and seven percent in langauage. These findings that household attributes strongly influence school performance in Latin America are consistent with findings in other settings. In most of the country-specific regressions, similar positive effects of two-parent households and education of the head are obtained, although the effects are sometimes imprecisely estimated.

However, by far the most consistent finding in all the countries and for both test scores is that child labor harms student performance, even when controlling for family, teacher and school attributes. The results are reported in the columns labeled conditional means in Table III.2.[5] While the advantage of children who almost never work relative to those who work often is attenuated somewhat, nonworking children enjoy a double-digit percentage advantage in test scores in every country except the Dominican Republic. On the other hand, the advantage of occasional workers over those who always work becomes insignificant in ten of 22 possible cases, although the advantage still exists in all but two cases. Therefore, children who work only part-time while in school lose almost as much in terms of lower cognitive achievement as children who work all the time.

Glewwe's (2002) review of studies of schooling and cognitive ability on earnings found that virtually all of the positive impact of education on wages comes through the impact of education on improved mathematics and language skills. Our estimates suggest that the average lost learning as a consequence of being in the labor market as a child is -15.4 percent in lost mathematics ability and -18.6 percent in lost langauage ability. The estimated reduction in adult wages as a consequence of being in the labor market as a child reported by Ilahi et al. (2003) was -20.3 percent. Consequently, the percentage loss in cognitive skills attributable to working while in primary school are quite consistent with the corresponding percentage loss in wages later in life.

III.VI. Conclusion

A consistently administered survey of 3^{rd} and 4^{th} graders, their parents, and their teachers over 11 Latin American countries reveals a startling fact - the most consistent predictor of performance on tests of mathematics and language in terms of sign and significance was whether the child engaged in work outside the home. Children who worked occasionally outperformed those who worked often when out of school, but the advantage to part-time workers was small. On the other hand, the advantage in test scores for children who almost never worked outside the home was 15 percent to 19 percent, even when controlling for parental, teacher and school attributes that might have been expected to be correlated with child labor. These estimates of the lost cognitive skills associated with child labor are consistent with estimates of the wage loss adults suffer from having worked as a child.

The estimates derived in this study must be viewed as preliminary. It is possible that weak students are more likely to enter the labor market as children so that child labor responds to test scores rather than causing them. In that case, the estimates we derive may be too large. A definitive test would require deriving estimates that correct for this potential endogeneity of child labor, a task we hope to take up in the near future. The consistency of the magnitude of the estimated child labor effect on achievement and the robustness of the estimates to the inclusion or exclusion of other factors in the current study suggest that the child labor effect is real and will not be reversed.

The policy implications from the finding that child labor lowers cognitive ability are profound. First, there is a cost to having children work but keeping them enrolled in school. Even occasional child workers face a substantial loss of school achievement as a result of their work. As Levison et al. (2003) demonstrate, child labor is chracterized by high transition rates into and out of the labor force, suggesting that the adverse consequences of occasional work outside the home are spread quite broadly among Latin American children. Second, the lost cognitive ability and implied adult earnings loss from working as a child are large enough to suggest that the expenses of combating child labor can be recovered in part from higher earnings of the children when they enter adulthood. Furthermore, double-digit gains in cognitive ability attributable to withholding a child from the labor market will be enough to raise many out of poverty as adults to the extent that improvements in cognitive ability have been strongly associated with adult wages.

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Table III.1 Representative Characteristics of the Country Samples.

Country	N	Child Labor[a] (%)	Rural[b] (%)	Private[c] (%)	Poor[d] (%)	Test Score Mathematics	Test Score Language
Argentina	4224	34.4	12.4	18.9	21.4	17.5	13.5
Bolivia	4879	56.9	25.8	32.2	35.6	15.5	10.8
Brazil	4374	36.4	16.2	21.7	52.9	17.2	13.0
Chile	4646	45.7	26.5	33.7	46.8	15.8	13.0
Colombia	4306	52.4	28.4	25.0	42.0	15.4	11.7
Cuba	3950	e	33.1	0	4.0	26.7	17.1
Dominican Republic	3729	51.8	33.1	28.2	40.3	13.1	9.9
Honduras	3746	41.6	54.1	11.5	59.8	12.4	9.8
Mexico	5038	43.7	34.7	19.6	24.7	16.2	11.4
Paraguay	4718	29.8	36.0	29.4	23.2	14.9	11.4
Peru	4298	57.1	29.1	22.4	69.1	12.9	10.6
Venezuela	3691	21.4	22.5	21.6	13.0	11.8	11.5
All Countries	51485[f]	40.0	29.2	22.4	35.9	15.8	12.0

[a] Child indicates whether s/he works outside the home sometimes or always when not in school. [b] Child lives in community with population below 2,500. [c] Child attends private school. [d] Observer characterizes community socioeconomic status as poor or very poor. [e] Missing observations. [f] The potential sample size is attenuated by lack of responses to questions. Children were asked about the amount of time they worked outside the home. Only 36,826 responses were obtained on that question.

Table III.2 Average Language and Mathematics Test Scores, By Country and Level of Child Labor.

	Mathematics Test (Maximum Score = 32)		Language Test (Maximum Score = 19)	
Country	**Unconditional**[a]	**Conditional**[b]	**Unconditional**[a]	**Conditional**[b]
Argentina				
Often[c]	16.0	16.0	12.3	12.3
Sometime[d]	17.6**[e]	17.6**	13.3**	13.5**
	(10.0%)[f]	(10.0%)	(8.1%)	(9.8%)
Almost Never[g]	18.9**	18.0**	14.5**	14.1**
	(18.1%)	(12.5%)	(17.9%)	(14.6%)
Bolivia				
Often	14.5	14.5	9.8	9.8
Sometime	15.1*	14.7*	10.4**	10.3*
	(4.1%)	(1.4%)	(6.1%)	(5.1%)
Almost Never	17.2**	15.6**	12.3**	11.6**
	(18.6%)	(7.6%)	(25.5%)	(18.4%)
Brazil				
Often	14.6	14.6	11.4	11.4
Sometime	15.9**	15.8**	12.1**	11.8
	(8.9%)	(8.2%)	(4.3%)	(3.5%)
Almost Never	18.7**	17.8**	14.0**	13.3**
	(28.1%)	(21.9%)	(22.8%)	(16.7%)
Chile				
Often	13.8	13.8	11.6	11.6
Sometime	15.0**	15.0**	12.6**	12.6**
	(8.7%)	(8.7%)	(8.6%)	(8.6%)
Almost Never	17.0**	16.5**	14.0**	13.6**
	(23.2%)	(19.6%)	(20.7%)	(17.2%)
Colombia				
Often	14.2	14.2	10.3	10.3
Sometime	15.6**	15.8**	11.5**	11.7**
	(9.9%)	(11.3%)	(11.7%)	(13.6%)
Almost Never	16.4**	16.1**	12.8**	12.6**
	(15.5%)	(13.4%)	(24.3%)	(22.3%)
Dominican Rep.				
Often	12.6	12.6	9.5	9.5
Sometime	13.3**	13.3*	9.7	9.5
	(5.6%)	(5.6%)	(2.1%)	(0%)
Almost Never	13.8**	13.1	11.1**	10.6**
	(9.5%)	(4.0%)	(16.8%)	(11.6%)
Honduras				
Often	11.8	11.8	9.1	9.1
Sometime	12.6**	11.0	9.7**	9.4
	(6.8%)	(-6.8%)	(6.6%)	(3.3%)
Almost Never	14.6**	13.2*	11.8**	11.9**
	(23.7%)	(11.9%)	(29.7%)	(30.8%)
Mexico				
Often	13.8	13.8	9.6	9.6
Sometime	15.1**	15.4**	10.6**	10.7**
	(9.4%)	(11.6%)	(10.4%)	(11.5%)
Almost Never	17.7**	17.1**	12.5**	11.8**
	(28.3%)	(23.9%)	(30.2%)	(22.9%)

Table III.2 (Continued)

Country	Mathematics Test (Maximum Score = 32) Unconditional[a]	Mathematics Test (Maximum Score = 32) Conditional[b]	Language Test (Maximum Score = 19) Unconditional[a]	Language Test (Maximum Score = 19) Conditional[b]
Paraguay				
Often	13.9	13.9	11.2	11.2
Sometime	15.5**	15.4	11.8**	11.8
	(11.5%)	(10.8%)	(5.4%)	(5.4%)
Almost Never	17.3**	18.0**	13.1**	13.1**
	(24.5%)	(29.5%)	(17.0%)	(17.0%)
Peru				
Often	11.6	11.6	9.1	9.1
Sometime	11.9	11.8	10.1**	9.7**
	(2.6%)	(1.7%)	(11.0%)	(6.6%)
Almost Never	14.9	13.4**	12.2**	10.7**
	(28.4%)	(15.5%)	(34.1%)	(17.6%)
Venezuela				
Often	12.2	12.2	10.0	10.0
Sometime	13.0*	12.9	10.9**	10.5
	(6.6%)	(5.7%)	(9.0%)	(5.0%)
Almost Never	14.5**	13.7**	11.5**	11.3**
	(18.9%)	(12.3%)	(15.0%)	(13.0%)
All Countries				
Often	13.6	13.6	10.2	10.2
Sometime	14.7**	14.4**	11.1**	10.9**
	(8.1%)	(5.9%)	(8.8%)	(6.9%)
Almost Never	17.0**	15.7**		12.1**
	(25.0%)	(15.4%)	(29.5%)	(18.6%)

[a] Simple mean test score over all children in the child labor group in the county. [b] Based on coefficients of dummy variables for "sometime" and "almost never" from country-specific regressions comparable to the specifications reported in Table III.4. The regressions also included all the school, teacher and household factors included in Table III.4. [c] Child almost always works outside the home when not in school. [d] Child sometimes works outside the home when not in school. [e] Indicates difference in mean test score from the "often working" group is significant at the 0.05(*) or 0.01(**) level of significance. [f] Percentage difference relative to children who often work outside the home when not in school. [g] Child never works outside the home.

Table III.3 Definitions and Summary Statistics for Exogenous Variables Included in the Analysis.

Variable	Description	Mean	Std. Dev.
Child Labor			
Sometime	Dummy variable indicating if child works outside the home occasionally when not in school.	0.33	0.47
Almost Never	Dummy variable indicating if child almost never works outside the home.	0.43	0.49
Household			
Two Parents	Dummy variable indicating there are two parents or legal guardians in the household.	0.80	0.40
Head Education	Average education level of the parents or legal guardians, indicated by an index with 1=primary incomplete, 2= primary complete, 3=secondary incomplete, 4= secondary complete, 5=tertiary incomplete, 6= tertiary complete.	2.74	1.63
Teacher			
Education	Education level of the teacher, indicated by an index with 0=none, 1=secondary, 3=tertiary.	1.45	0.56
Experience	Years the teacher has been teaching .	13.80	8.90
School			
Rural	Dummy variable indicating if the school is located outside an urban area.	0.29	0.45
Public	Dummy variable indicating school is not a government school.	0.75	0.43
Single Grade	Classroom only includes a single grade.	0.90	0.30
Pupils/Classroom	Number of pupils in the classroom.	31.00	12.40

Notes: Sample excludes Cuba and drops observations with missing data on child labor.

Table III.4 Pooled Educational Production Function Estimation.

Variable	Mathematics	Language
Child Labor		
Sometime	0.80**	0.70**
	(7.12)	(9.11)
Almost Never	2.06**	1.85**
	(18.7)	(24.6)
Household		
Two Parents	0.38**	0.23**
	(3.61)	(3.12)
Head Education	-0.07	0.18**
	(0.67)	(2.54)
$(\text{Head Education})^2$	0.12**	0.05**
	(7.29)	(4.53)
Teacher		
Education	-0.16	0.31
	(0.42)	(1.15)
Education^2	0.15	-0.04
	(1.04)	(0.40)
Experience	0.00	-0.00
	(0.25)	(0.39)
School		
Rural	-0.39**	-0.91**
	(3.63)	(12.1)
Public	-1.77**	-0.85**
	(15.7)	(11.1)
Single Grade	-0.30*	-0.10
	(2.08)	(0.98)
Pupils/Classroom	0.00	0.00
	(0.63)	(1.07)
Country Dummies	Included	Included
R^2	0.18	0.21
N	18373	18375
Mean of dependent variable	14.90	11.60

** indicates significance at the 0.01 confidence level. * indicates significance at the 0.05 confidence level. T-statistics in parentheses.

Endnotes

[1] In the United States, teacher experience also appears important, but teacher education does not matter.
[2] See Glewwe (2002) for a comprehensive review of the problems associated with estimating educational production functions.
[3] For a detailed description of the a priori exclusions in each country, consult Table III.6 of the Technical Bulletin of the LLECE.
[4] Official statistics are not available, but CIA estimates of the Cuban GDP per capita in 2000 was $1700. That is one-third the per capita GDP of Honduras and Bolivia and about one-seventh the per capita GDP of Argentina. For estimates for all countries, see http://www.cia.gov/cia/publications/factbook/.
[5] The R-square for individual country estimates were of like magnitude to those reported in Table III.4 for the sample as a whole.

Chapter IV. Child Labor, School Achievement and Endogenous Household Decision Making: A Multinational Study

A paper to be submitted to a journal in the field.

Victoria Gunnarsson

IV.I. Abstract

This paper identifies the most important factors that determine child labor and employs the findings to identify the effect of working while in school on achievement. In contrast to previous studies that find similar evidence, this study controls for the simultaneous household decision-making process, considers a much larger set of countries and thus generates results that are more applicable worldwide. In sum, I conclude that academic achievement can largely be explained by the amount of work that the child performs outside the household and that local household, teacher, school and community characteristics also play important roles in deriving estimates of the impact of child work on learning. Most importantly, I find that instrumenting for child labor generates much larger adverse impacts of child work on school performance that previous exogenous models.

IV.II. Introduction

Child labor is generally seen as undesirable. Nevertheless, despite of the worldwide consensus that young children's work has damaging health effects, threatens the child's physical and psychological development and increases the instances of poverty, around 10-15 percent of the world's children work. In many more cases work is part-time and combined with schooling. In Chapter II we found that the incidence of child labor across countries can be largely explained by per capita income, the relative importance of agriculture to GDP and the level of adult literacy in the country. Agriculture's share of GDP has a large significant positive effect on the child labor rate in the country while income per capita and adult literacy have significant negative effects. These results lead me to investigate other factors than increased standard of living when determining the causes and consequences of child labor in countries with relatively high income. It is also important to realize that the economics of child labor works differently in different parts of the world and something that alleviates the incidence of child work for some countries does not necessarily display the same effects elsewhere.

The relationship between child labor and income is shown in Figure II.2. This convex relationship suggests that as economic growth raises average income in a country, child labor declines at a decreasing rate. In Latin America, average per capita income is now high enough that child labor has become relatively insensitive to further income gains. Hence, the income levels in Latin America (and other countries studied in this paper) fall in the flat portion of the curves in Figure II.2. Therefore, improvements in income alone are unlikely to eliminate child labor in countries with income levels such as in Latin America. Factors that influences child labor, other than income changes, must be identified. My analysis will concentrate on local factors such as household, teacher and school characteristics.

The trade-off between schooling and child labor is widely presumed. Parents make decisions whether or not to send their children to school based on the extent of the opportunity costs of schooling in terms of foregone earnings. Schooling becomes an investment alternative and a way to transfer income from parents to children. Especially in rural families in developing countries, children are pecuniary assets; a source of current income or, if the parents choose to invest in schooling, a way to achieve greater economic stability in the future given mutual altruism. Parents may, to a high degree, depend on their children as the parents get older. High expected returns to investment in children's schooling are important if the parents' welfare will depend on their children's income as adults. As societies modernize and social security and other benefits become more important to parents' income status later in life, the returns to schooling of children are not directly tied to parents' utility. More likely, in modern societies parents care about their children's schooling because they care about their children's welfare but not directly related to their own. In developing countries, education is one of the most important ways of securing a future with an improved quality of life as well as accumulating human resources contributing to national economic development. This is the reason why reduced returns to schooling are viewed as one of the most harmful impacts of child labor.

Moreover, Rosenzweig and Evenson (1977) suggest that marginal price effects, associated with the economic contribution of children, in the allocation of family resources to schooling are important. The results also show that variables that are positively related to the economic returns to child labor – size of land-holdings, agricultural productivity and child wage rates – also appear to be positively related to child labor-force participation and therefore negatively related to child schooling. Because most working children are also enrolled in school, the presumption of the trade-off between schooling and child labor is not necessarily consistent with observed actions. The consequences of part-time child labor on schooling or school attainment are difficult to assess. In order to measure these, the opportunity costs of schooling have to be weighed in as well. In many employment categories, especially in developing countries, obtaining on-the-job-skills may be as important as attending formal schooling if the type of work available in the area of residence is labor intensive and requires experience in that particular field. However, Nobel laureates like Gary Becker and James Heckman both stress that the mastery of lower levels of material is a prerequisite to assimilating more advanced knowledge and that "learning begets learning". (Lord, 2002). Using the Ben-Porath (1967) model of human capital accumulation it can be shown that human capital brought into adulthood increases the productivity of subsequent learning efforts and that human capital investments (schooling) increase lifetime wealth. Empirically, a study of human capital accumulation for the Spanish labor force showed that workers with higher formal education accumulate human capital through learning by doing at a faster pace than less educated workers (Fernandez and Mauro, 2000). Moreover, Abdulai and Delgato (1999) found positive and significant effects of number of years of formal schooling on both husbands' and wives' non-farm wages in Ghana, while work experience had a positive but diminishing effect. These results lead me to presume that schooling, both in industrialized and in developing countries, has a greater positive impact on adult opportunities than obtaining on-the-job skills. Moreover, Becker (1975) claims that firm specific training increases a worker's marginal revenue production (MRP) at a faster rate than obtaining no training, while general training increases MRP at an even faster rate. Applying this theory to child labor research, specific training can be viewed as human capital that the child obtains in the child labor market while general training can be thought of as formal primary or secondary schooling. Therefore, schooling must be viewed as the best alternative to accumulating human capital and early entry to the labor force will ultimately lower skill levels. Only one study (Vijverberg, 1999) found that the impact of education, measured either by years of school attendance or by cognitive skills, on non-farm self-employment income was small. The study concludes that the impact of education on non-farm self-employment is complex and probably varies by the type of business and it is therefore premature to draw any general conclusion from this study alone.

On the other hand, child work is not always detrimental to schooling. For example working when school is not in session does not interfere with learning and in agricultural areas, children may even get time off from school during the harvest season when additional labor is critical. Even though child work may or may not compete with schooling, working when young still remains harmful for the child's physical as well as mental development. Nonetheless, when combining work and schooling, children may be too tired to study, which decreases the quality of learning efficiency. In addition, children who already contribute economically to the family often lack motivation and are less interested in academic achievement affecting the child's own future prospects (Heady, 2000).

In contrast to the findings in Chapter II and Heady (2000) who find similar evidence, this study controls for simultaneous household decision-making and employs a much larger set of countries and thus generates results that are more applicable worldwide. In sum, I conclude that academic achievement can largely be explained by the amount of work that the child performs outside the household and that local household, teacher, school and community characteristics also play important roles in assessing the effects of child work on academic achievement. Most importantly, I find that instrumenting for child labor generates much larger adverse impacts of child work on school performance that previous exogenous models.

IV.III. Literature Review and Theory

Most of the studies up to this point have focused on the relationship between child labor and school attendance rather than school attainment. Neri et al. (2003) conclude that a child should attend school if the present value of the wage increase attributable to schooling exceeds the cost of child time in school. However, attendance is not an ideal measure to determine the harm of child labor on learning. On the one hand, it may over-estimate the negative effects of child work, ignoring the poor quality of many schools in developing countries as children may receive better informal or on-the-job training outside school. On the other hand, using attendance as a measure of the damage of child work as children combine school and work (the case especially in Latin America) could lead to an over-estimate of the accumulation of human capital because even though the child attends school, working takes away valuable study time and makes the child too tired to learn.

Ravallion and Wodon (2000) argue that child labor has no adverse consequences for human capital development because increases in enrollment are not associated with appreciable decreases in child labor. Others show that child labor is associated with greater grade retardation (Sedlacek et al., 2003) and lower attained schooling (Psacharopoulos, 1997) so that the adverse consequences are apparent in attained years of schooling, if not enrollment. Nevertheless, schools might not apply the same uniform standards in enforcing grade repetition or promotion, so age-grade distortions or repetition are not perfect indicators of learning.

Another possibility is that child labor retards the learning process, even if the child remains in school, and that the amount of human capital produced per year of completed schooling decreases. This is consistent with findings by Ilahi et al. (2003) that working as a child is associated with lower returns to schooling and a greater incidence of poverty as an adult. This can be thought of as taking away from length of schooling by early entry into the labor force. Moreover, studies by Glewwe (1996) and Moll (1998) found that cognitive skills, as opposed to years of schooling, are the fundamental determinants of adult wages.

The majority of studies attempting to analyze the relationship between child labor and school attainment focus on the U.S. and on working while in high school or college. A review of the results of these studies which find little evidence that part-time work combined with schooling hurts school achievement as long as the job does not occupy too long hours, can be found in Chapter III.

As discussed in Chapter III, the impact of working while in high school or college in highly developed countries may be very different than that for young children working in developing countries where supplementing the family's income by working while in school can be crucial to the family's survival. School attainment is presumed to decrease as child labor increases because working while in school disturbs the learning of basic numeracy and literacy. The more the child works, the lower the school attainment. Test scores are a measure of school attainment and will in this paper serve as the indicator of students' academic achievement.

Chapter III, using the same information on 3rd and 4th graders in Latin America as is used in this paper, found that the most consistent predictor of student performance on mathematics and language tests was whether the child was engaged in work outside the home or not. However, because of the difficulty of taking into account the child's innate ability, the results may be distorted due to the self-selection of strong students to school and weaker students to the labor market. The role of endogeneity in the relationship between child labor and schooling is important. If child labor could be a result of schooling outcomes rather than causing school outcomes, the negative correlation between school achievement and child labor may be incorrectly attributed as a consequence rather than a cause of child labor. In this paper I attempt to correct for endogeneity by instrumenting for child labor when predicting the effects on school achievement.

One study that mainly focuses on the effect of child work on school enrollment also evaluates the effects of hours of work on human capital accumulation in Pakistan and Nicaragua (Rosati and Rossi, 2001). In contrast to Chapter III, Rosati and Rossi derive and estimate a simultaneous equation system that accounts for the household's decision relative to the school enrollment and to the hours worked by the child. On the contrary, academic achievement is measured in terms of falling behind in school. The results from the study, although completely ignoring teacher and school quality characteristics, indicate that the amount of hours worked, not merely the fact that a child is working, are an important determinant of school achievement both in Pakistan and Nicaragua even though these countries exhibit very different patterns in child labor and school enrollment in general.

Heady (2000), using information from the Ghana Living Standards Measurement Survey found that child work had relatively little effect on school attendance but had a substantial effect on learning achievement in reading and mathematics. The effect remained strong even after controlling for the child's innate ability using the Raven (1967) test. The study found that the majority of the effect of working on learning achievement is direct: because of exhaustion or lack of interest in academic performance holding education constant, rather than indirect: the effect that work has on schooling attendance.

This study goes beyond the single country analysis by employing two multi-country data sets, results of which are more encompassing in identifying the relationship between child labor and schooling world-wide. Furthermore, compared to Heady (2000) who takes child labor as given, this study seeks not only to explain the impact of child labor on student test scores but attempts to explain child labor itself.

IV.IV. Conceptual Framework

In this paper, the presumption that the incidence of child labor affects the child's attainment in school is tested by analyzing two unique data sets. First, I treat child labor as exogenous and incorporate it into an equation predicting student achievement in school. Next, child labor is treated as endogenous. By predicting child labor using variables that are presumed not to directly affect student achievement and then incorporating this predicted measure into an equation of school performance, the effect on child labor on school attainment is evaluated.

Glewwe (2002) characterizes parental utility, as positively related to lifetime consumption and to their children's cognitive skills. He also expresses the production of skills as a function of years of schooling and school quality where the child's cognitive skills (acquired human capital) times the productivity of these skills in the labor market are taken into account. Cognitive skills, in turn, are modeled in terms of a simple production function whose arguments are school quality, years of schooling and a learning efficiency coefficient. Consequently, if the learning efficiency can be interpreted as the amount of knowledge the child absorbs in school it is easy to comprehend that what the child actually learns in school is directly tied to how successful the child will be when entering the labor force. Specifically the mechanism through which cognitive skills are acquired can be written as

$$I = Qf(S)g(Y) \tag{IV.1}$$

where I symbolizes cognitive skills, Q is the learning efficiency coefficient, $f(S)$ is a function of school quality and $g(Y)$ is a function of years of schooling. Henceforth, I will discuss how Q is determined.

Child labor is related to a bundle of child, household, teacher, school and community characteristics. Following Hanushek (1986), I measure students' academic achievement (test score), Q, as a function of attributes of the student's household, H, the student's teacher, T, the student's school and school quality, S. To this I add attributes of the type of community the student resides in; rural versus urban, C, student age, A, student gender, G, compulsory schooling laws in each country, L, and past accumulation of cognitive achievement from prior schooling or from unmeasured ability, X. Because agriculture is the heaviest occupier of child labor, children living in rural areas are assumed to be more inclined to work than children in urban areas. Moreover, it has been shown that the incidence of working when young increases with age and that boys work more outside the home than girls. Older children are more physically and mentally able to work than younger children. Also, boys are in general stronger than girls and thus more suitable for physical work than girls. Furthermore, because many cultures find it inappropriate for girls to do physical work, girls tend to work less outside the home and more in unpaid household chores that are not as easily measured as paid work. The legal environment in each country that controls the ages children should be in school are also presumed to influence academic achievement because of its influence on parents' decision of how much the child can work. In addition, one important factor for girls' child labor and schooling in developing countries is the age at which they get married. In countries where women get married at an early age, the returns to schooling may not be valued highly and the amount of time spent working instead of learning is presumed to be higher.

Because work and school are not predetermined but rather results of complex household choices, the joint functions measuring child labor and student academic performance by child i taught by teacher j in school k, community l and country m, can be written as

$$CL_{ijklm} = f_1\left(W_{ilm}, A_{ijklm}, G_{ijklm}, H_{ijklm}, T_{jklm}, S_{klm}, C_{lm}, L_m, Q_{ijklm}; \varepsilon_{ijklm}\right) \qquad \text{(IV.2)}$$

$$Q_{ijklm} = f_2\left(A_{ijklm}, G_{ijklm}, H_{ijklm}, T_{jklm}, S_{klm}, C_{lm}, CL_{ijklm}, X_{ijklm}; \varepsilon_{ijklm}\right) \qquad \text{(IV.3)}$$

where combinations of A, G, H, C, and the legal environment variable, L, are instruments and affect school attainment through the child's likelihood of working. ε_{ijklm} is a random disturbance term. Child labor, CL, is determined by the unobserved wage in the child labor market, W, age, gender, household, teacher, school, community and country level variables discussed earlier and the measure of the student's achievement in school, Q. Because the child's wage is determined by age, gender and the type of community in which the student lives, these variables can be thought of as proxies for W. In turn, academic achievement or test scores also depend on the amount that the child works, CL. As can be seen, the endogenous nature of the schooling and child work decisions play an important role in measuring the effects on child work on schooling outcomes. In a study on wages, Blackburn and Neumark (1993) argue that neglecting to control for unobserved innate ability on wages, estimates of the increase in schooling returns could reflect a change in the schooling-ability relationship. Their model predicts that failure to control for ability in a wage regression should result in upward-biased estimates of returns to schooling. In the case of child labor and schooling there is similar reason to believe that failure to account for the student's innate ability would bias the effects of child work on test scores because of the simultaneous household decision process. There are several ways of attempting to control for ability. Heady (2000) uses the outcome of a Raven test that measures students' innate ability. For the two data sets employed in this paper no such tests were available. Another possibility to control for ability would be to study the behavior of siblings since their household characteristics are identical, however, there is no student-household identification link available for either of the data sets used. Parental attributes may be viewed as proxies for missing ability if ability is inherited and will be studied in greater detail in the school-level analysis discussed in section IV.IX.

The essence of the endogeneity problem caused by the self-selection of strong and weak students to schooling or work, is that it is difficult to tell whether it is work that determines school attainment or school attainment that determines the extent of child labor. One possibility is that weak students drop out of school as they enter the labor market. The possible reverse relationship from schooling to work can be eliminated by using exogenous instrumental variables. Applying the discussion in Heady (2000) to my analysis, this can be illustrated by assuming that there is a correlation between the child labor variable, *CL*, and the error term in equation (IV.3) because of failure to realize that stronger students are more likely to attend school than students with lower performance in school or lower innate ability. This negative error in *CL* leads to higher than expected *Q*, which in turn biases the estimated absolute value of *CL* in (IV.2) to a level lower than what would otherwise be expected. This effect generates a positive correlation between the error term and the predicted *CL* in (IV.3) as the coefficient on *CL* picks up the effect that is really due to the error term. The result is that, due to omitting measures of past school performance or innate ability, the estimated coefficient on *CL* in (IV.3) is biased and less negative than it should be. Using exogenous instrumental variables, variations of age, gender, community and legal variables, which are not presumed to be correlated with ability or test scores, eliminates some of the correlation between the child labor variable and the error term that was found by simple residual analysis.

In general, it is expected that parents' education, both through increased information about costs and benefits of schooling and through increased income, has negative effects on child work but positive impacts on school attainment. Teacher characteristics such as teacher education and experience are usually important to student achievement in developing countries (Hanushek, 1995). However, results by Hanushek (1986) suggest that only teacher education contributed to student achievement while years of experience, high school grades and mean salary had little effect on achievement. Quality of educational material such as school buildings and access to textbooks and instructional supplies also tend to impact student attainment in a positive direction (Hanushek, 1995).

It is possible that factors that raise learning in school would also raise earnings potential out of school. However, if the local child labor market does not value school achievement, but only values the physical labor that a child can perform, then factors that improve learning will not also raise the opportunity cost of schooling. A study by Rosenzweig (1980) found that in 1960s and 70s rural India, wage rates were not importantly affected by human capital attributes in the non-salaried, private-sector occupations characterizing the rural local labor market. Rather, physical stature is an important factor that determines wages in the local market. Hence, variables that are related to physical stature but not child learning will be good prospects for instruments for child labor.

IV.V. Data

IV.V.I Latin America

The data used in this paper come from two different sources. The first data set comes from the Latin-American Laboratory of Quality of Education (LLECE) who in 1997 administered the First Comparative International Study on Language, Mathematics and Associated Factors in Latin America. The data set is discussed in more detail in Chapter III. A description of the variables used in the Latin America analysis in this chapter can be found in Table IV.1a. The designation (C) indicates that the information was obtained from the student questionnaire, (P) from the parents' questionnaire, (T) from the teachers' and (Pr) from the school principal. Summary statistics for the mathematics and language data sets are reported in Table IV.2a and IV.2b.

IV.V.II TIMSS

The second data source in this paper is from a project by the International Study Center at Boston College. The Third International Mathematics and Science Study (TIMSS) from 1995 is the largest international study of student achievement ever conducted. During 1994-95, the test was administered at five different grade levels in more than 40 countries worldwide. The grades tested used for this paper were grades seven and eight suggesting average student ages of around 14 years of age. While testing students in mathematics and science a large information set from students, teachers and school principals was also collected. For this paper, because it focuses on developing countries, Colombia, Czech Republic, Hungary, Iran, Latvia, Lithuania, Romania, Russia, Slovak Republic and Thailand were chosen because they were the poorest countries tested. All these countries fall in the lower middle-income class or the lower part of the upper middle-income class classification from the 1998 World Development Report. Thus, similar to the Latin America countries, child labor in these TIMSS countries should also be relatively insensitive to further gains in per capita income. No countries from the low-income class were tested. The test was also administered in Argentina, Bulgaria, Indonesia, Kuwait, Mexico, Philippines and South Africa. However, several important variables were missing for these countries excluding them from the analysis all-together. A description of the TIMSS data variables used in the analysis is reported in Table IV.1b. The TIMSS data consist of several files. Student, parent and household characteristics were taken from the student background file (indicated by (C) in Table IV.1b), teacher information comes from the teacher background file (indicated by (T) in Table IV.1b) and school and community information comes from the school background file (indicated by (Pr) in Table IV.1b because questions were answered by the principal at each school). Summary statistics of the variables used in the TIMSS analysis can be found in Table IV.2c.

Moreover, information on compulsory school starting and ending ages as well as information on whether a year of preprimary education is required in each country was added to instrument for child labor. This information was obtained from the UNESCO Institute of Statistics' *Education Statistics 2001-Regional Report on Latin America* and from Right to Education. The information on the percentage of women between the ages of 15 and 19 that are married are obtained from the United Nations. The third type of instrument is a measure of legal authority taken from Kaufmann, Kray, and Lobaton (2002) who derive estimates of the political environment of each country. The variables used are political stability: the likelihood that the current government system will persist, the quality of the country's regulations on private enterprise, and the confidence people have in the country's ability to enforce the laws.

For two variables, inadequacy (Latin America) and shortage (TIMSS), factor analysis was employed to create an aggregated index of school shortages since both surveys contain multiple measures of the level of school material sufficiency. The questions in the Latin America survey included were whether or not the teachers judged classroom lighting, classroom temperature, classroom hygiene, classroom security, classroom acoustics, language textbooks, math textbooks and all textbooks to be adequate or not. For TIMSS principals were asked the extent to which the school experienced shortages in instructional material, budget for supplies, school buildings, heating and lighting and instructional space. The adequacy (shortage) of school supplies measure is the weighted sum of these responses where the weights were taken as the first principal component of the teachers' or principals' responses. In both data sets, the greatest shortages were for instructional materials. Wealthier schools should have superior facilities and educational materials and it is expected that schools lacking vital supplies to efficiently educate their students are poorer quality schools and hence inadequacy or shortage of school supplies would increase child labor because of lowered returns to schooling and decrease test scores because of the lower educational quality.

Child labor generally takes on two forms: unpaid work in the household or in a household farm or enterprise, and outside work in the paid labor market. In this paper only paid work outside the home is used as a measure of child labor. For the Latin America data, in answering the question of how regularly children work outside the home, children could choose from three alternatives: "almost never", "sometime" and "often". In the TIMSS data children answered the question how much they worked at a paid job during each day by "never", "less than 1 hour", "1-2 hours", "3-5 hours" or "more than 5 hours". The concentration on work outside the home is due in part to the presumption that the child's assessment of work away from home is likely to be more accurate because it regimes a disruption of the house routine. Furthermore, the debate over the harmful effects of child labor generally does not include working in the home. Nevertheless, because girls are much more likely to do house work than boys, excluding housework from the analysis disregards essential gender issues as an explanatory factor in the household decision making process.

Finally, an important factor to note is the selected nature of the data. Because the tests and questionnaires were given only to children who attended school, no information was obtained from children who are not in school. Hence, children who only work or devote their time to leisure are not included in the analysis. It is thus not possible to extend any conclusions to children who do not attend school. Nonetheless, as the majority of working children are enrolled in school, the bias is likely to be modest.

IV.VI. Child Labor and Schooling – Country Differences

When analyzing and interpreting the results from the analysis of the two data sets it is also critical to realize the cultural, economic and social differences between the groups of countries. As a very interesting side analysis Heady (2000) compares child labor and schooling in three very diverse countries; Ghana, Pakistan and Bangladesh. He concludes that combining working on the household enterprise and going to school is much more rare in Pakistan than in Ghana and virtually unknown for girls. Wage work clearly interferes with schooling in Pakistan so that child work is competing with school attendance in Pakistan to a much greater extent than in Ghana. In Bangladesh, the difference between girls' and boys' school attendance is much smaller than in Pakistan but work participation rates are not found to be much different than in the other two countries. However, it is even less common to combine schooling and work in Bangladesh than in Pakistan and a large part of this is explained by the fact that children are much more likely to work outside the household in Bangladesh. These results illustrate that the interaction between child labor and schooling work very differently for different countries and that policy intervention must be designed according to the context of the country. Latin America experiences a much higher school enrollment rate and lower work participation than in either of the African or Asian countries. This phenomenon is probably due to relatively higher levels of income per capita and partly to greater urbanization. The urbanization in Latin America reduces the opportunities to work within the household or family farm and those children who do work are more easily able to also attend school.

Furthermore, seven of the ten TIMSS countries in our sample are formerly planned economies in central Europe. These countries differ greatly in income, culture and industrial mix from the farm based traditional economies in Africa and Asia and alters the household decision making process whether to send a child to work or to school from that in Latin America. The differences between the TIMSS and the Latin American samples are substantial, so it is possible to test the robustness of the results in different country contexts.

IV.VII. Analysis of Variance

As discussed in the introductory section of this paper, Chapter II explains child labor as a function of real income per capita, agriculture's share of GDP and adult literacy level. All these variables are at the country level. Given that this analysis includes multiple levels of data in each set; student and household level, teacher level, school level, community level and country level, it is useful to analyze how much of the variation in child labor and school achievement that can be attributed to variation across countries versus within countries. It might be expected that the incidence if child labor in a country would in part be formed by the country's legal structure for child work and schooling. Regressing child labor on a complete set of country dummy variables found that only three percent of child labor in the Latin America data set could be explained by differences across countries. In the TIMSS data set, four percent of the variation in child labor could be attributed to differences across countries. In other words, 96-97 percent of the variation in child labor occurs within countries, emphasizing the importance of local factors rather than national policies when it comes to combating child labor.

Likewise, in order to analyze the variability in school achievement, test scores were regressed on a set of country dummy variables. In the Latin America data set only eight percent (both mathematics and language) of the variation was explained by the ANOVA regression which leaves 92 percent of the variation in test scores within countries. For TIMSS, 27 percent (mathematics) and 23 percent (science) of the variance in test scores was attributable to cross-country variation. Although this is substantially higher than for Latin America, it indicates that the vast majority of the variation in school achievement can be explained by intra-national factors. The fact that the cross-country variation in tests scores is so much higher for the TIMSS countries than the ones in Latin America can most likely be attributed to the great geographical and cultural dispersion in the TIMSS countries compared to the fairly homogenous group of Latin American nations. It may also be possible that the school systems in the TIMSS countries are more developed with less variation in school quality within countries. Similarly, Vegas (2001) concludes that in Chile, variation in student outcomes and school inputs were typically greater within than between sectors. Differences in student socioeconomic background are responsible for much of the variation between schooling sectors (defined as municipal, private voucher, private paid and catholic voucher schools respectively). In my study, because it deals with two large sets of countries with different sectorial divisions, no sector or school level analysis of variance is performed. Instead, regression analysis will explain the sources of variability within countries.

IV.VIII. Empirical Strategy

The first step in the estimation process is to predict child labor. I rely on child age as an indicator of the opportunity cost of schooling. Separate age effects are estimated for boys and girls, for urban and rural children, and across countries with differing regulations on ages when children must be in school. Experimentation showed that the age effect was constant below 10 years of age. A dummy, d10, indicating if the child age is nine or below is used to measure the average effect of young age on probability of working. In TIMSS, a similar strategy is employed, using a dummy variable, d13, for children 12 or below in that sample. As ten years is also the approximate age that children should be in 3^{rd} and 4^{th} grade the dummy variable also signals unusually young children. The measure of child labor is an ordered index from 0-2 in Latin America (and 1-5 in TIMSS). Ordered data is a special case of discrete choice data where the outcome is ranked. The OLS, multinomial logit and multinomial probit models fail to account for ordinal data (Greene, 1997). Nonlinear least squares (NLS) and weighted nonlinear least squares (WNLS) are feasible estimation models but suffer from relative inefficiency (Ruud, 2000). Instead the ordered probit model has become popular in analyzing ordered response data and is likewise used to predict child labor intensity in this study.

One may regard the qualitative responses to question how much the child works as ordinal categorical measures of an underlying continuous variable. The model is built around the latent regression

$$y_i{*} = x_i{'}\beta + \varepsilon_i, \quad \varepsilon_i \sim \mathrm{N}(0, \sigma) \qquad \text{(IV.4)}$$

for all individuals *i*, *i = 1,…N*. $y_i{*}$ is the latent variable and is an unobservable index of child labor intensity, x_i is a vector of explanatory variables (including A, G, H, T, S, C, L) and ε_i is a random error term. In the Latin America data, what we do observe is

$$y_i = \begin{cases} 0 \ \ if \ -\infty \leq y_i{*} \leq \alpha_1 \\ 1 \ \ if \ \ \alpha_1 \leq y_i{*} \leq \alpha_2 \\ 2 \ \ if \ \ \alpha_2 \leq y_i{*} \leq +\infty \end{cases} \qquad \text{(IV.5)}$$

where α_js are unknown threshold parameters to be estimated with β.

Specifying that ε_i has the c.d.f. $F(\cdot)$ and that the probability that $y_i = j$ is the probability that $y{*}_i$ falls into the $(j+1)^{\text{th}}$ interval of the p.d.f., the probability that y_i equals the value *j* (*j = 0, 1,…J*) for each step in the step c.d.f. becomes

$$\begin{aligned} \Pr\{y_i = j \mid x_i\} = \Pr\{\alpha_j \leq y_i{*} \leq \alpha_{j+1}\} &= \left\{\frac{\alpha_j - x_i^{'}\beta}{\sigma} \leq \varepsilon_i \leq \frac{\alpha_{j+1} - x_i^{'}\beta}{\sigma}\right\} \\ &= F\left(\frac{\alpha_{j+1} - x_i^{'}\beta}{\sigma}\right) - F\left(\frac{\alpha_j - x_i^{'}\beta}{\sigma}\right) \end{aligned} \qquad \text{(IV.6)}$$

where α_0 and α_{J+1} are defined so that $F(\alpha_0) = 0$ and $F(\alpha_{J+1}) = 1$ and $\alpha_{J+1} = \infty$. When α_js are parameters, the ordinal probability model does not identify σ separately from the α_js and β but the ratio α_j / σ is like an intercept for each probability term in the likelihood function. Hence, no intercept for $x_i^{'}\beta$ is identified (Ruud, 2000).

The log-likelihood function equals

$$\sum_{i=1}^{N}\sum_{j=0}^{J} 1\{y_i = j\}\log\left[F\left(\frac{\alpha_{j+1} - x_i^{'}\beta}{\sigma}\right) - F\left(\frac{\alpha_j - x_i^{'}\beta}{\sigma}\right)\right] \tag{IV.7}$$

and the probability of a child being in each of the three child labor intensity groups (*j*s) can be estimated by maximizing the log-likelihood function for each of the *j*s.

The magnitude of the ordered probit coefficient does not have a simple interpretation, but its sign and statistical significance are the same as in the linear regression model. In the case of child labor a positive coefficient indicates higher child labor frequency as the value of the associated variables increase. Negative signs suggest the opposite (Wooldridge, 2002). Because of the complicated interpretation of the βs it is difficult both to obtain and to interpret elasticities. Instead Beta-coefficients are calculated and are discussed below. For a more exhaustive discussion about ordered probit estimation see Greene, 1997 or 2000, Ruud, 2000 or Wooldridge, 2002. The first stage results for the Latin America data are reported in Table IV.3 and for TIMSS in Table IV.5.

Next child labor, first exogenously and then predicted, is inserted into the test scores equation, (IV.3). The results of this ordinary least squares estimation are shown in Table IV.4 and Table IV.6. After instrumenting for child labor the signs of the coefficients of the exogenous variables in equation (IV.3) indicate the direction of the indirect effects of household, teacher characteristics etc. on school performance while the sign of the coefficient on work represents the direction of the direct effects of the explanatory variables in (IV.2) on academic performance through the effect of working. Because using the predicted value for child labor in the second stage does not take into consideration the first stage regression the standard errors in Tables IV.4 and IV.6 were obtained using bootstrapping methods.

IV.IX. Results

IV.IX.I Latin America

IV.IX.I.A Child Labor

The results as a whole from analyzing the Latin America data come out as expected. Many of the instruments in Table IV.3 prove to be individually insignificant, however, joint tests of the null hypothesis that the level of the instruments and the interacted effects of these variables are jointly equal to zero show that the instruments are jointly highly significant. Chi^2-test statistics of the variables Age, Boy, Rural, Comp Start Age, Comp End Age, Preprimary and d10 all show significance at the one percent level except Comp Start Age in the language data set which is significant only at the five percent level. Note that the coefficients from an ordered probit regression are not equal to the marginal effects of the regressors on the dependent variable. Because child labor is measured by an ordered variable which divides the children into distinct groups with progressively higher workloads it is awkward to work with marginal effects related to specific work intensities. However, the signs of the coefficients in Table IV.3 and IV.5 represent the direction of the partial effect of the child, household, teacher, school, community and legal environment surrounding the child on the intensity of work.

In order to more closely evaluate the effect of the interaction term instruments on child labor joint tests of these variables were performed as above but now also evaluated at sample means. For instance, in evaluating the significance of being a boy, all terms including

Boy evaluated at the sample means of the interactions were jointly tested. These tests indicate strong joint significant effects on the probability of working of being a boy, living in a rural area and having mandatory preprimary education. In addition, age and compulsory starting age were also significant at the five percent confidence level while compulsory ending age of schooling failed to significantly contribute to explain child labor. Figures IV.2a-d and IV.3a-c show the effect on child labor of age in different scenarios for Latin America. The graphs were constructed by first obtaining index functions of child labor from the sum of the coefficients in the child labor equations evaluated at sample means. Then the index functions were normalized at zero at the age of six (11 for TIMSS).

The incidence of working increases with age until the child reaches 14 years of age however, the probability of working increases at a decreasing rate. It is interesting to note that in the Latin America sample, child labor seems to drop off at the age of 14 for rural children while urban children still experience increasing rates of work above the age of 14. Keeping in mind that we are only measuring work outside the household, and because Latin America is relatively highly urbanized, children that reach the age of 14 could be forced to leave school in the rural areas to find work for higher pay in the cities. Hence, for the children who stay in the rural areas and continue schooling they are not as likely to work as those who live in urban areas. The likelihood of working decreases in rural areas and is surpassed by the likelihood of working in the more urbanized zones. On the other hand, the number of children above 14 years of age in 3rd and 4th grade is very small (3% of the sample in the mathematics data and 2% of the sample in the language data) so conclusions of this kind cannot be made with very high certainty. In addition, children not enrolled in school are not observed so nothing can be concluded regarding children who only work and do not attend school.

As can be seen in Table IV.3, not attending preschool increases the likelihood of child labor however without significance in the mathematics data analysis. Parents' education, the number of books in the household, and having parents who speak Spanish (Portuguese in Brazil) as their mother tongue reduce the likelihood of child labor. Parental education, number of books in the household and Spanish speaking parents can be interpreted as proxies for household income. Their negative impact on the likelihood of working while in school suggested by these results are consistent with numerous studies, including Chapter II, which find that child labor incidence falls with household income or parental human capital. Even though child labor in Latin America has become relatively insensitive to increases in average income, increasing household income for those in the lowest quintiles would lower child labor. This effect has to be interpreted with respect to the size and type of the community in which the student resides. Urban schools tend to have higher enrollment than schools in rural areas due to population size differences. Since we know that child labor is more common in rural and agricultural areas where schools are generally smaller, it is difficult to compare the effect of enrollment frequency without specifying the size of the community in which the school is located. Moreover, inadequacy of school supplies seem to lower the quality of education and raises the likelihood of child work. Furthermore, as the number of available mathematics or language classes increases, the likelihood of working decreases.

Teacher and school level determinants can be interpreted as indicators of the quality of education in a school. Having poor teachers and poor quality of school supplies such as textbooks, lighting and security in the school lowers the return to education and thus increases the incentive for parents to send their children to work more frequently. The only counter result is the positive effect of teacher education on child labor. Teacher education increases school quality and thus should lead to lowered likelihood or working.

Examining the results of the legal structure variables living in a country with a high degree of regulatory quality has a strong positive effect on child labor while rule of law decreases the incidence of working. Political stability exhibit significant but mixed results in the mathematics and language data sets. The frequency of young married women in a country has interesting impacts on the incidence of child labor. In the mathematics data, where the outcome indicates that boys generally are more likely to work than girls, marriage turns out to be insignificant while in the language data set, where the effect of being a boy on the incidence of working is not significant, marriage has a positive effect on child labor. It is clear that there is a difference in the structure of child labor and schooling as the likelihood for young women to get married increases. As expected, if women are more likely to get married young, the likelihood of working increases.

Moreover, comparing boys and girls the likelihood of working is higher for boys than for girls (Figures IV.1a and IV.2a). Requiring children to start school at an early age showed ambiguous effects as did the effect of having mandatory preprimary education in a country. The presence of schooling laws dictating that schooling is mandatory at age five compared to at age seven actually produced higher probability of working in the mathematics data set (Figure IV.1c). Not requiring a preprimary year raised the likelihood of working in the mathematics data set while is showed decreased probability of work in the language data set (Figures IV.1d and IV.2d). The information on starting ages comes from schooling laws in the respective countries. However, nothing is known about well these laws are enforced.

IV.IX.I.B Child Work Treated as Exogenous

Examining Table IV.4, child labor is highly significant when it is treated as exogenous as well as when it is treated as endogenous. First, I discuss what is obtained when equation (IV.3) is estimated directly without attempting to correct for endogeneity. Modeling child labor exogenously (the first two columns in Table IV.4) boys did better than girls on the mathematics test while girls did better than boys on the language test, supporting generally accepted findings that boys do better on mathematics related topics and girls are stronger in language. The effect of working outside the home also has a slightly larger effect on mathematics scores than language scores. This could be due to the fact that boys are more likely to do work outside of the household than girls who generally are employed within the household lowering the effect of outside work on language achievement. To compare the sensitivity of the changes in both data sets Beta coefficients were calculated. At the average, mathematics scores decreased by 0.16 standard deviations from a one standard deviation increase in working while language scores decreases by 0.19 standard deviations. The Beta coefficients reported in this paper were calculated by multiplying the coefficient of working, β_{CL}, by the ratio of the standard deviation of working, σ_{CL}, and the standard deviation of test scores, σ_Q. Because the ordered probit regression predicts values of child labor that can take negative values even though the ordered choice variable only ranges from 0-2 (1-5 in TIMSS), mean of predicted child labor cannot be directly used to calculate elasticities.

In addition, the older the student the better the test scores. However, the positive effect of age on school achievement can most likely be explained by the difference in the skill level between third and fourth graders. Because the same test was given to both grades, fourth graders are likely do better than the children who on average have had one year less of both education and maturity. Not attending preschool lowers test scores. Parents' education, number of books at home and having parents that spoke Spanish (Portuguese) when young have positive effects of school attainment.

Among the teacher level determinants the results suggest that male teachers produce worse students than female teachers while the level of teacher education has mixed results. At the school level attending a school with a large number of children enrolled increases test scores. Living in a rural area also lowers school attainment compared to the results of children living in urban and metropolitan areas. For the mathematics data set, children living in urban areas but with less than one million people did better on the test than children in metropolitan areas. For the language test, the effect was also positive but insignificant at the five percent level.

IV.IX.I.C Child Work Treated as Endogenous

The two-stage regression using instrumented child labor, column three and four in Table IV.4, give similar results. However, the effect of the child's work outside the home are much stronger (more negative) than in the first two columns. At the mean, mathematics scores decrease by 0.41 standard deviations from a one standard deviation increase in working outside the home while language scores fall by 0.55 standard deviations; much greater negative impacts that what the exogenous model displayed. This is a consequence of having taken into consideration the simultaneous decision making process in the household. The student's age, being a boy and going to preschool have positive effects on academic performance. However, in contrast to the exogenous model the outcome of parents and household variables becomes weakened or insignificant and there seems to be no significant effects from teacher gender, inadequacy of school supplies or number of mathematics or Spanish (Portuguese) classes per week. The puzzling finding that teacher education lowers mathematics test scores but raises language scores remains the same as in the exogenous model. The effect of the community variables are mixed.

IV.IX.II TIMSS

IV.IX.II.A Child Labor

The results of the analysis of child labor in the TIMSS data are presented in Table IV.5. In contrast to the Latin America sample there is only one data set including both mathematics and science scores hence only one column in Table IV.5.

All instruments in the TIMSS sample are jointly significant from zero. The relationship between child labor and age in the TIMSS sample is described in Figures V.3a-c. The likelihood of working is a positive function of age for the TIMSS countries. Also, the likelihood of working living in an urban area surpasses that of rural areas at the age of 17 but the difference is only marginal. As in the Latin America sample, the likelihood of working is higher for boys than for girls (Figure IV.3a). Also consistent with the analysis of the instruments in the Latin America language sample, the TIMSS study showed negative effects on child work of requiring children to start school at an early age (Figure IV.3c). No information on preprimary education was available for the TIMSS sample.

In sum, for both Latin America and TIMSS it is clear that boys work more than girls, rural children work more than children in urban areas and the probability of working long hours increases with age. These findings support results from previous studies discussed in the literature review (section IV.III). Nevertheless, work beyond the age of 14 years of age (17 for children in the TIMSS study) seem to be more commonly located in urban areas and the likelihood of working actually lessens with age in rural areas at this age.

Among the exogenous variables the level of father's education, speaking the language of the test, living with both parents and number of books the family has at home decrease the likelihood of working. The effect of mother's education is also negative but surprisingly insignificant. Having a young, male teacher seems to increase the likelihood of working but the level of teacher education has no significant effects on child labor. As for the school level variables, attending a large school with a large share of girls enrolled decreases the probability of working, i.e. small, all boys schools seem to increase the probability of working while in school. Again, one has to take into consideration the type of community (urban versus rural) in which the school is located to completely understand the effects of school size and child labor. In contrast to the Latin America analysis, shortage of school supplies like textbooks and school buildings has no significant impact on the likelihood of child work. Class size, however, seem to be negatively related to the probability of working.

The indicators of the legal structure of the country exhibit completely different effects than in the Latin America data most likely due to the great heterogeneity between the groups of countries examined. In the TIMSS data, the degree of political stability and regulatory quality both have negative effects on the child labor while rule of law is positively correlated with working. The occurrence of married women between the ages of 15 and 19 has no significant effect on child labor. Women marrying young is also much less common among the TIMSS countries, nine percent, than among the Latin American sample, where the same figure is 17 percent (see Tables IV.2a-c).

V.IX.II.B Child Work Treated as Exogenous

Determining the impacts of child labor on test scores, Work Paid (how often the child was working at a paid job) was modeled both exogenously and instrumented as in the Latin America data. The results of treating child labor exogenously are shown in the first two columns in Table IV.6 both indicating a strong negative effect of engaging in paid work on test scores. In the TIMSS data average mathematics and science scores decrease by 0.07 and 0.06 standard deviations respectively from a one standard deviation increase in work at a paid job. As in the Latin America analysis, age improves test scores, and boys do better than girls on the mathematics test and also on the science test. The level of mother's and father's education as well as living with both parents and having many books at home have positive effects on school achievement while living with a large number of people in the household seem to lower academic performance. Interestingly, students who frequently speak the language of the test at home performed worse on both tests compared to students who speak another language at home, although only 3.5 percent of the children in the TIMSS data reported that they never speak the test language at home. Furthermore, older and better-educated teachers produce better students and male teachers are outperformed by female teachers. Larger classes are better for learning but the total number of enrolled students in the school gives mixed results. Finally, children living in rural areas did better than students in urban areas in the mathematics test. However, community size appears as insignificant in the science test equation.

IV.IX.II.C Child Work Treated as Endogenous

Results controlling for endogeneity are reported in columns three and four of Table IV.6. Instrumenting child labor does not markedly change the effects of the exogenous variables. However, the estimated effect of child labor becomes much larger. The Beta coefficients are as high as –0.12 and –0.16 standard deviations for average mathematics and science scores from a one standard deviation increase in child labor.

In general, the findings from the regression analysis coincide very well with what was presumed. Estimating the exogenous effect of child labor on test scores under-estimates the effect of the coefficient on child work so that the predicted harm of working while in school is not strong enough. Modeling child labor as an endogenous outcome allowing for self-selection reflects the true effect of child labor on academic achievement. This effect proves to be much stronger and more detrimental to children's learning than previously believed.

The country level determinants, although significant, show no clear trends across the three data sets and can thus not be relied on in order to describe the relationship between child work and academic performance in a country. Much more likely and proven by the results of the analysis of variance in section IV.VII, household and community characteristics are key players when judging to what extent combining work and schooling hurts the child's ability to accumulate basic numeracy and literacy skills.

IV.X. Robustness

Two side analyses are performed in order to verify the robustness of the results in the previous section. The first spotlights the household level determinants of child labor holding school and community effects constant. The second divides the rural and urban variables into smaller sub-units and compares the likelihood of working and the effect on test scores for children in rich and poor neighborhoods.

IV.X.I School Level Analysis – Focusing on the Household

Because the theory of child labor emphasizes the importance of household level determinants when allocating the child's time between work and school, I focus on the relationship at the average school level work and test result. Holding beyond teacher level variables constant, the school level analysis focuses on within-community attributes, given the school, community and country in which the student resides. In moving from a random effects model to a fixed effects model two possible methods are used. First, I regress the difference between the individual student's work and the school average child labor on the remaining child, household and teacher variables. Secondly, instead of subtracting the school average work in the dependent variable, I use it as a regressor. This second method serves as a consistency check on the more common fixed-effects estimator and produces virtually the same results as the first method.

In the second stage, I use the exogenous measure of the difference between the individual student's work and the school average work per day as well as the predicted value from the regression of the deviation of the individual student's work from the school average child labor on the remaining child, household and teacher variables to obtain an estimate of the extent to which child labor harms academic performance. In essence, this analysis is an extension of the analysis of variance in section IV.VII as the remaining variance after the school level analysis can be attributed to differences beyond the child, household and teacher levels.

By creating a dependent variable that is the difference between the individual student's test score and the school average score a new measure of achievement is created that holds constant school, community and country level characteristics that could influence the student's performance. The child labor and test scores equations can be written as

$$D_{ijklm} = f_1\left(W_{ilm}, A_{ijklm}, G_{ijklm}, H_{ijklm}, T_{jklm}; \varepsilon_{ijklm}\right) \tag{IV.8}$$

$$V_{ijklm} = f_2\left(A_{ijklm}, G_{ijklm}, H_{ijklm}, T_{jklm}, D_{ijklm}, X_{ijklm}; \varepsilon_{ijklm}\right) \tag{IV.9}$$

where $D_{ijklm} = CL_{ijklm} - CL_{klm}$ is the difference between student work, CL_{ijklm}, and the school average CL_{klm}. Similarly, $V_{ijklm} = Q_{ijklm} - Q_{klm}$ represents the deviation of the student's test score, Q_{ijklm}, from the school average score Q_{klm}. ε_{ijklm} is a random disturbance term. Because taking the difference between the individual student's score and the school mean generates a continuous dependent variable ordinary least squares estimation can be employed in the child labor equation. Technique number two modifies equation (IV.9) to

$$Q_{ijklm} = f_2\left(A_{ijklm}, G_{ijklm}, H_{ijklm}, T_{jklm}, D_{ijklm}, Q_{klm}, X_{ijklm}; \varepsilon_{ijklm}\right) \tag{IV.10}$$

Table IV.7 and Table IV.8 show the results from this exercise for the Latin America data. Similarly, Table IV.9 and Table IV.10 present the TIMSS sample outcomes. For both Latin America and TIMSS, the school level study on child labor performed according to the first method (column one and two in Table IV.7 and column one in Table IV.9) lacks explanatory power. The Pseudo-R^2 for the three child labor equations are low (only one percent) and most of the regressors are insignificant. Joint tests however, display that terms including Boy and Age are jointly significant from zero at the five percent level. Pursuing the second method and keeping school average child work as an explanatory variable results in a few more individually significant coefficients and improves the overall fit of the model to about 9-10 percent in both the Latin America and TIMSS samples. The significance of the second technique serves to evaluate the robustness of the first technique since at first glance it does not appear to be very successful in predicting child labor.

Explaining school achievement however, generates decent results even though the individual regressors in the child labor equation are mainly insignificant. In all six test score equations in Table IV.8, average level of child labor per school comes in as strongly negatively related to test scores. When modeling the effect of child labor on academic performance endogenously the sensitivity of test scores from a one standard deviation increase in work becomes much stronger. The –0.11 and –0.15 standard deviation reduction of average mathematics and language scores grow to around –0.15 and –0.20 standard deviations respectively from a one standard deviation increase in child labor. In Table IV.10 the TIMSS data analysis shows that the effect of working at a paid job reduces test scores. Exogenously mathematics and science scores fall by around 0.07 to 0.05 standard deviations from a one standard deviation increase in work. The two endogenous models testify of reductions in test scores of between 0.25 and 0.32 standard deviations from a one standard deviation increase in working at a paid job.

Moreover, boys do better than girls on mathematics and science while girls outperform boys in language. Fourth and eighth graders do better than third and seventh graders respectively. Parents' education, especially mother's education, has a positive impact on school performance as do the number of books the student's family possesses. Teacher variables produce mixed results.

In sum, fixing the effects of school, community and country variables minimizes the noisiness of the community determinants while the results reinforce the findings from the main analysis. Following the analysis of variance results that showed that more or less all of the variation in child labor and test scores are within countries it is also clear that much of this within country variation is also within communities. While school and community variables are significant determinants of the impact of working on school achievement, they are secondary in nature behind the child specific and household attributes.

IV.X.II A Closer Look at the Community

In the Latin America data set, the community variable describing the type of community in which the school is situated takes on three different values; metropolitan, urban and rural. In addition to this variable, there is another community variable which, in contrast to the general community variable which only describes the size of the community, provides a more detailed description of the environment surrounding the schools by also distinguishing between rich and poor areas. The reason why this variable is not used in the main analysis is because several principals did not respond to the question. The detailed community variable is divided into eight different answer alternatives. The principal could choose to portray the area in which the school is situated as a; an developed zone in the country's capital (with paved streets, sewage, running water and electricity), b; a marginal zone in the country's capital (without or with few paved streets and lacking certain services such as sewage, running water or electricity), c; an developed zone in a secondary city (100,000 inhabitants or more), d; an marginal zone in a secondary city (100,000 inhabitants or more), e; a town (between 100,000 and 5,000 inhabitants), f; a village (between 5,000 and 500 inhabitants), g; a rural area close to a town (less than 500 inhabitants and less than 50 km from a town), h; a distant rural area (less than 500 inhabitants and more than 50 km from a town).

Table IV.11 and IV.12 depicts the regression results when the detailed geographic/socioeconomic community measures are introduced as instruments in the child labor regression. The variables are formatted as dummy variables equal to one if the school is located in the area and zero otherwise. The distant rural area alternative is excluded from the equation and serves as the baseline. The results in Table IV.11 indicate that children attending a school in the capital, a secondary city, or in a town are significantly less likely to work than children in a geographically isolated area. Attending a school in a village or in a rural area does not change the likelihood of working compared to students in an isolated area. An interesting observation is that the coefficient on Capital Developed and City Developed are more negative and more significant than the coefficients on Capital Marginal and City Marginal. This implies that children in relatively rich zones are less likely to work than children in schools in marginal zones. Hence, not only the size and location of the community matters in determining whether the children are likely to work a lot or not but also how socio-economically developed the area is.

Table IV.12 shows the result of the school achievement regression, modeling child labor both exogenously and instrumented as before. The results are strikingly similar to those obtained in the main analysis in Table IV.4. Using the geographic/socioeconomic community variables does not affect the outcome of the test scores prediction which confirms the robustness of the results from the main analysis. However, it has important explanatory power in determining child labor. Because the TIMSS data only define the community variable in terms of urban versus rural location, no detailed community analysis could be performed on the TIMSS data set.

IV.XI. Conclusion

The analyses of the relationship of child labor and school achievement in Latin America and the TIMSS data both point at the same results. Working while in school in the primary and middle school years has negative impacts on academic performance. Consistent with the underlying theory, modeling child labor exogenously as well as endogenously show that failure to account for the simultaneous household decision making process biases the effect of child labor on test scores. When child labor is instrumented for, the model incorporates self-selection issues allowing weak students to be more prone to work and devote less time to learning and thus reflects the true effect of working while in school. The endogenous model results in much more negative effects of child labor on school attainment than treating work outside the home as a given. Examining the Beta coefficient of the effect of work on test scores strengthens the argument. When child labor is instrumented for, the Beta coefficient of work effects on school achievement increase markedly in magnitude no matter which model is applied. The size of the estimated effect is consistent across all models and certifies the robustness of the results.

Furthermore, the results suggest that national mandates are inefficient in controlling child labor. Almost all of the variation in the amount of time that children spend working as well as the variation in academic achievement of the students can be attributed to within country factors. Among these, household level attributes appear to be the most important followed by the size and type of community in which the student resides.

The results of this analysis supports previous findings (for instance Chapter III) suggesting that policy design should take into account the effect of child work on cognitive skills as the student later on enters the labor market as an adult. Having worked outside the home during the primary and middle school years lowers attainment and thus lowers cognitive skills likely to harm adult earnings and standard of living.

The effect of working inside the home, especially common for girls, remains untreated. Incorporating household work in the analysis will cast additional light on the extent of the effect of child labor on schooling outcomes and will help distinguish gender differences in the accumulation of cognitive skills. Chapter V attempts to separate the effects of within household and outside the home work, however, the data set used (TIMSS) does not contain enough information on household work to draw any certain conclusions on the effects of this type of work on school achievement. Of interest to future research work, the new TIMSS Repeat 1999 examines students in 3rd and 4th grade in several more developing countries and could serve for an interesting comparison of possible changes in the effect of child labor and test scores over time.

IV.XII. References

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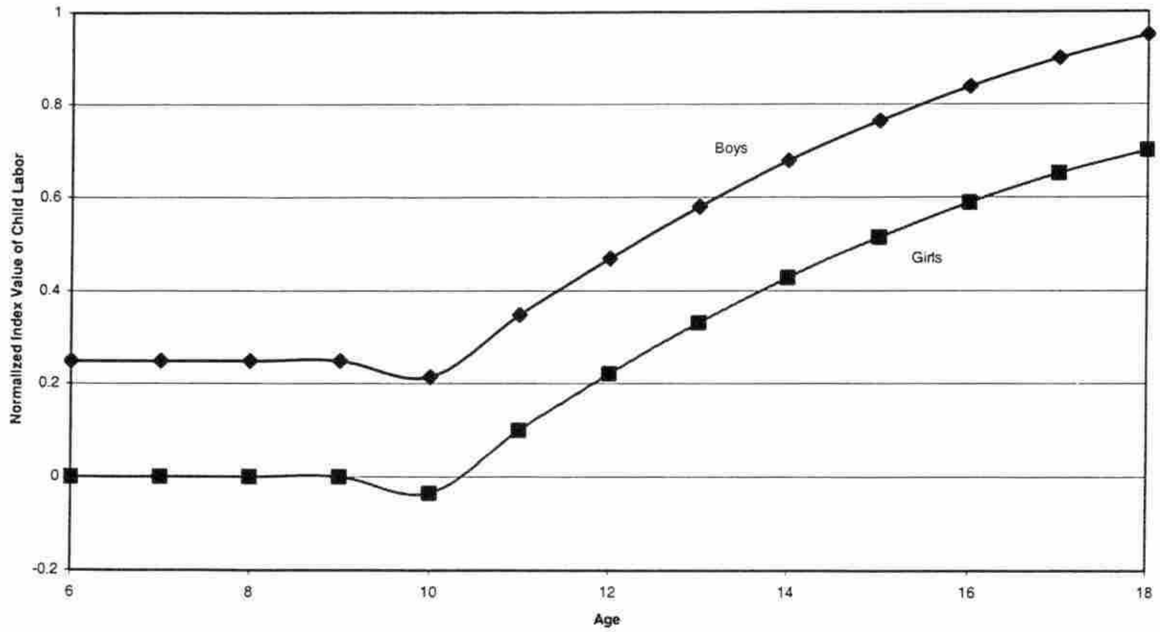

Figure IV.1a The Likelihood of Working and Age Between the Genders, Mathematics, Latin America Sample. Based on Predictions Reported in Table IV.3.

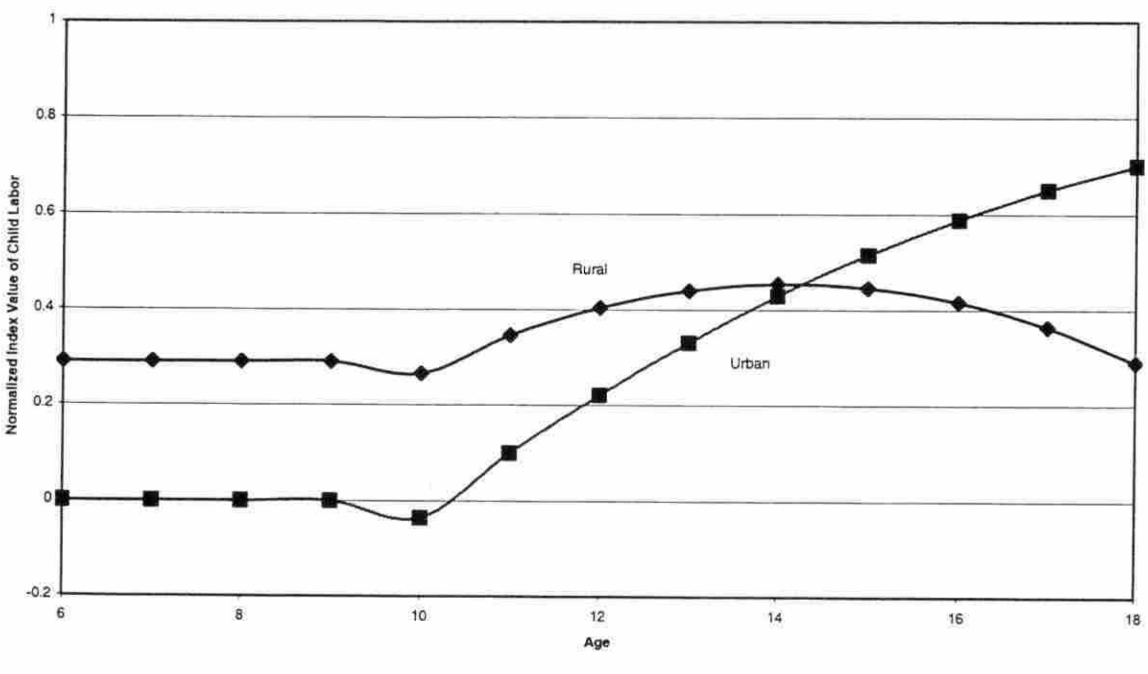

Figure IV.1b The Likelihood of Working and Age Between Communities, Mathematics, Latin America Sample. Based on Predictions Reported in Table IV.3.

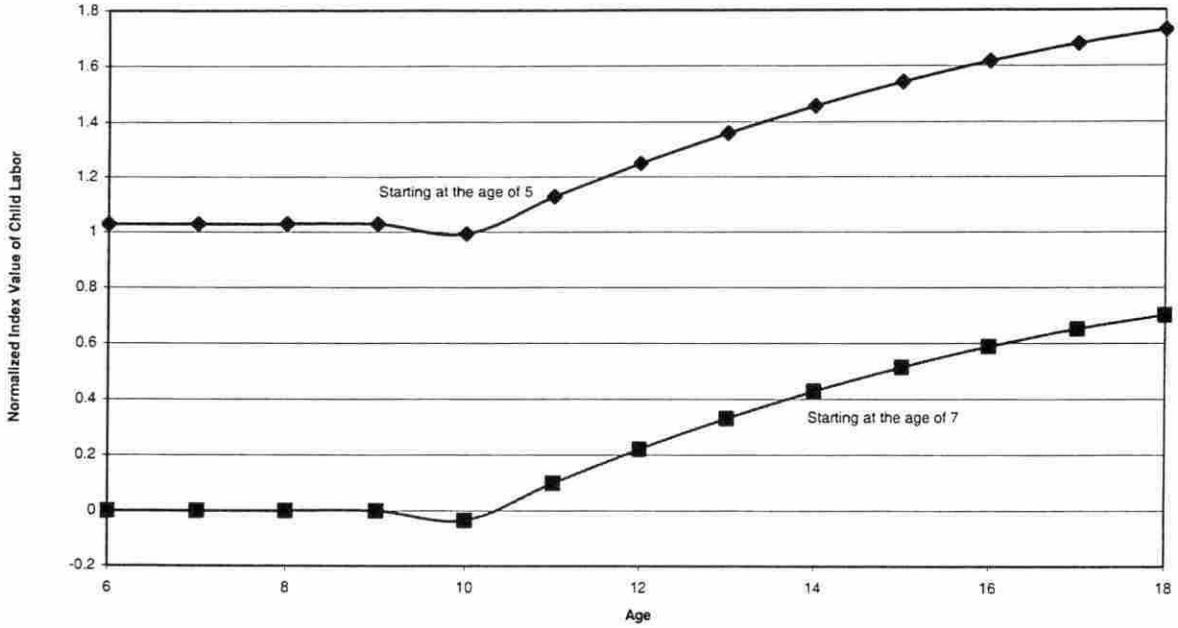

Figure IV.1c The Likelihood of Working and Age with School Start Ages, Mathematics, Latin America Sample. Based on Predictions Reported in Table IV.3.

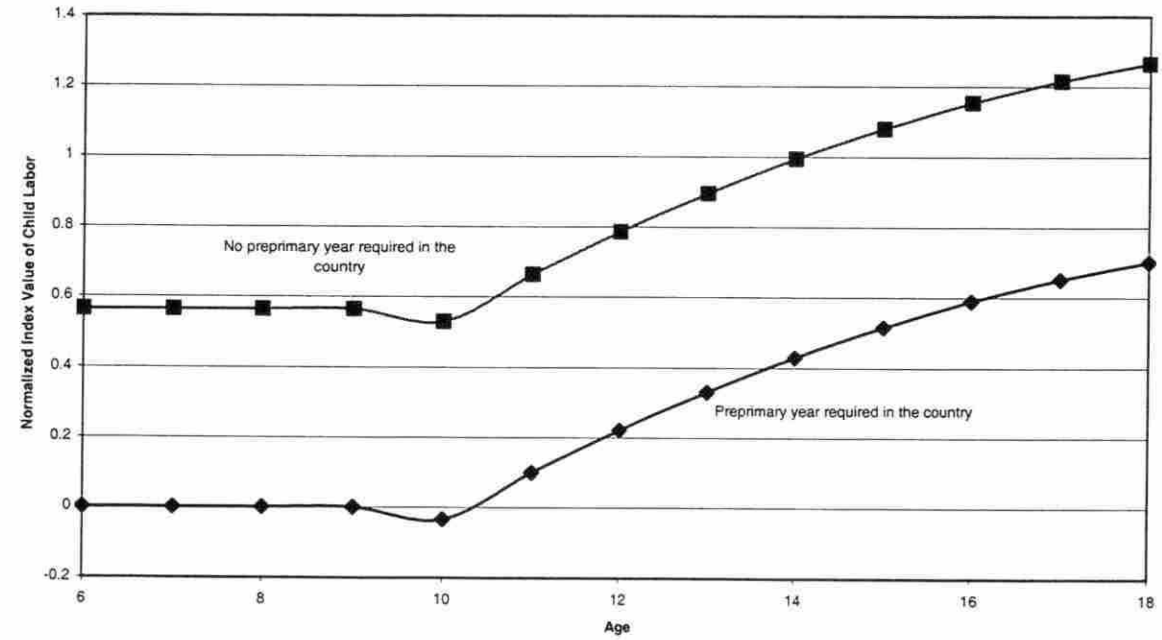

Figure IV.1d The Likelihood of Working and Age with a Preprimary Year, Mathematics, Latin America Sample. Based on Predictions Reported in Table IV.3.

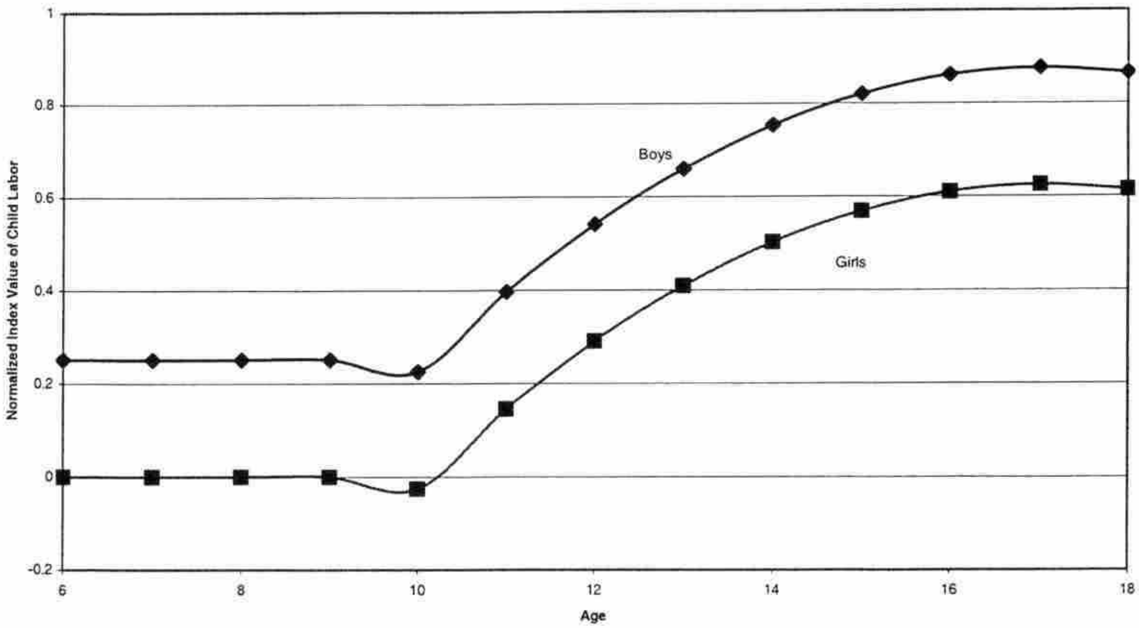

Figure IV.2a The Likelihood of Working and Age Between the Genders, Language, Latin America Sample. Based on Predictions Reported in Table IV.3.

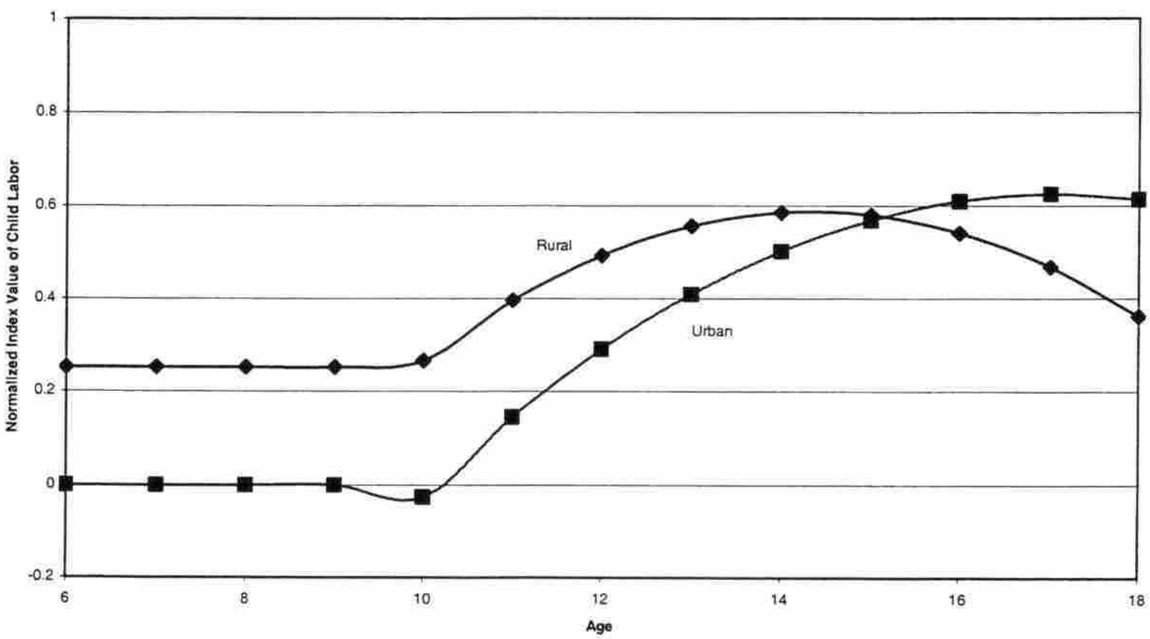

Figure IV.2b The Likelihood of Working and Age Between Communities, Language, Latin America Sample. Based on Predictions Reported in Table IV.3.

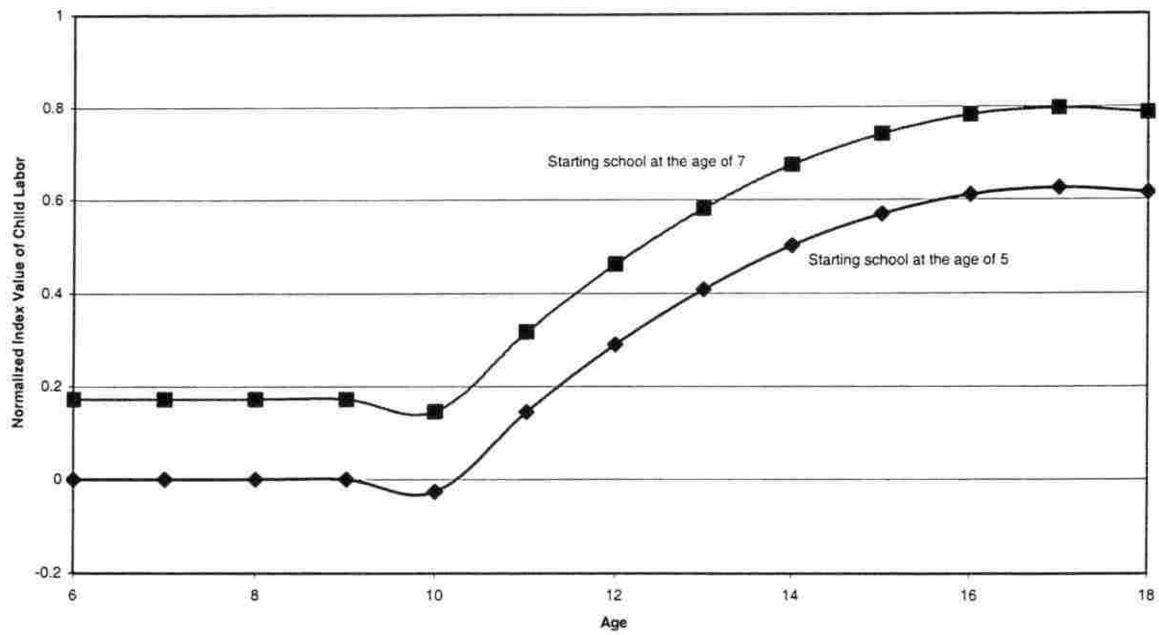

Figure IV.2c The Likelihood of Working and Age with School Start Ages, Language, Latin America Sample. Based on Predictions Reported in Table IV.3.

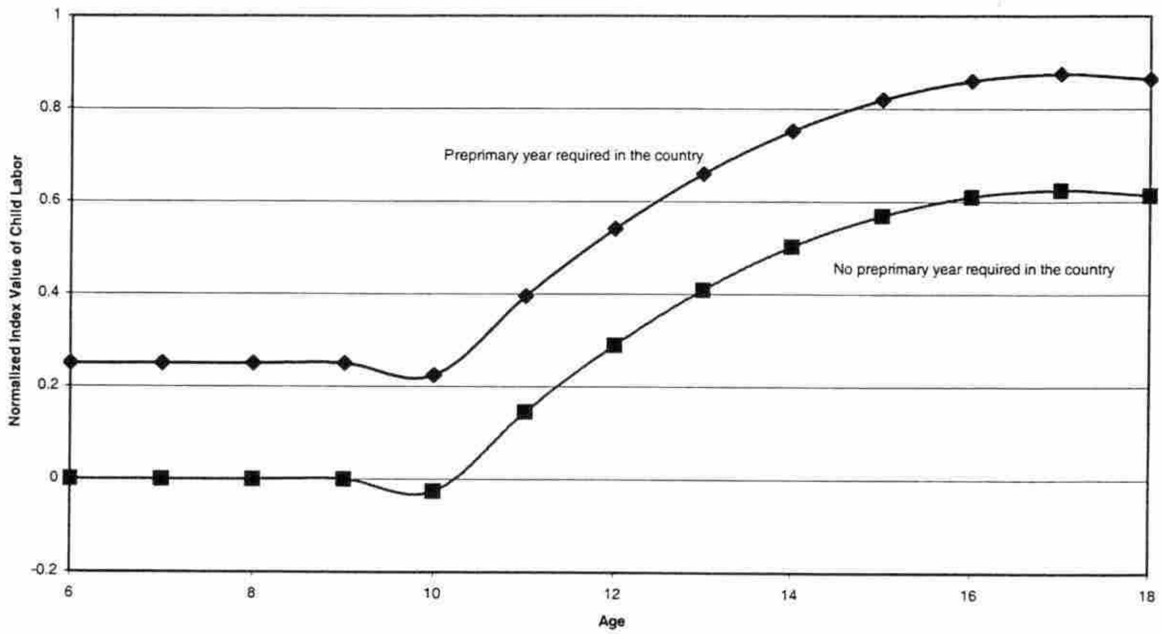

Figure IV.2d The Likelihood of Working and Age with a Preprimary Year, Language, Latin America Sample. Based on Predictions Reported in Table IV.3.

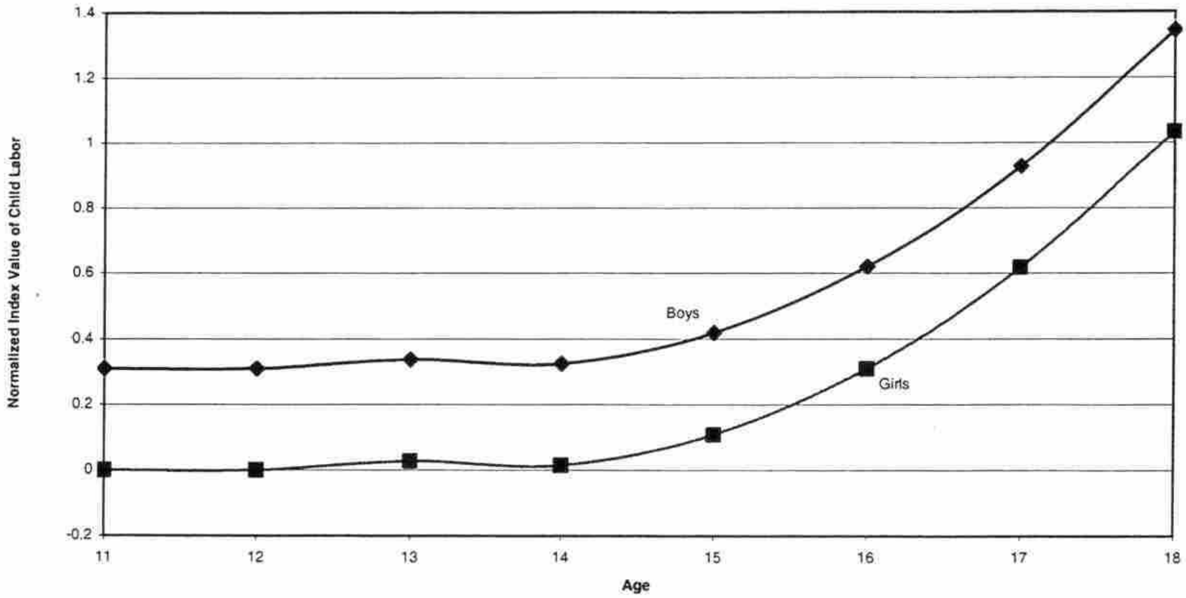

Figure IV.3a The Likelihood of Working and Age Between the Genders, TIMSS Sample. Based on Predictions Reported in Table IV.5.

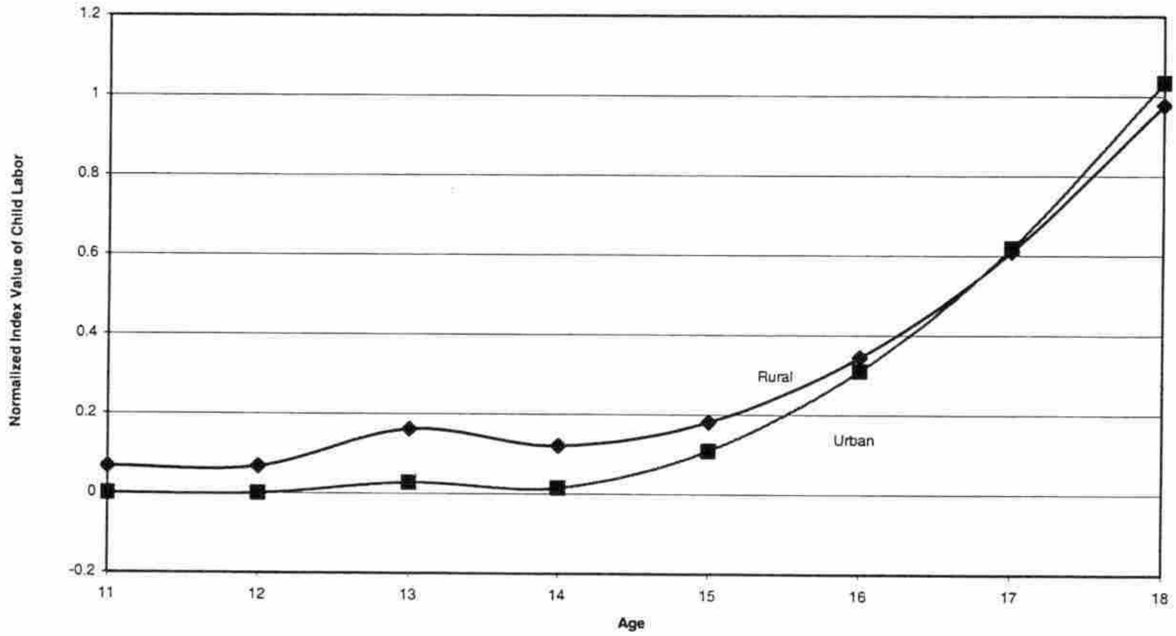

Figure IV.3b The Likelihood of Working and Age Between Communities, TIMSS Sample. Based on Predictions Reported in Table IV.5.

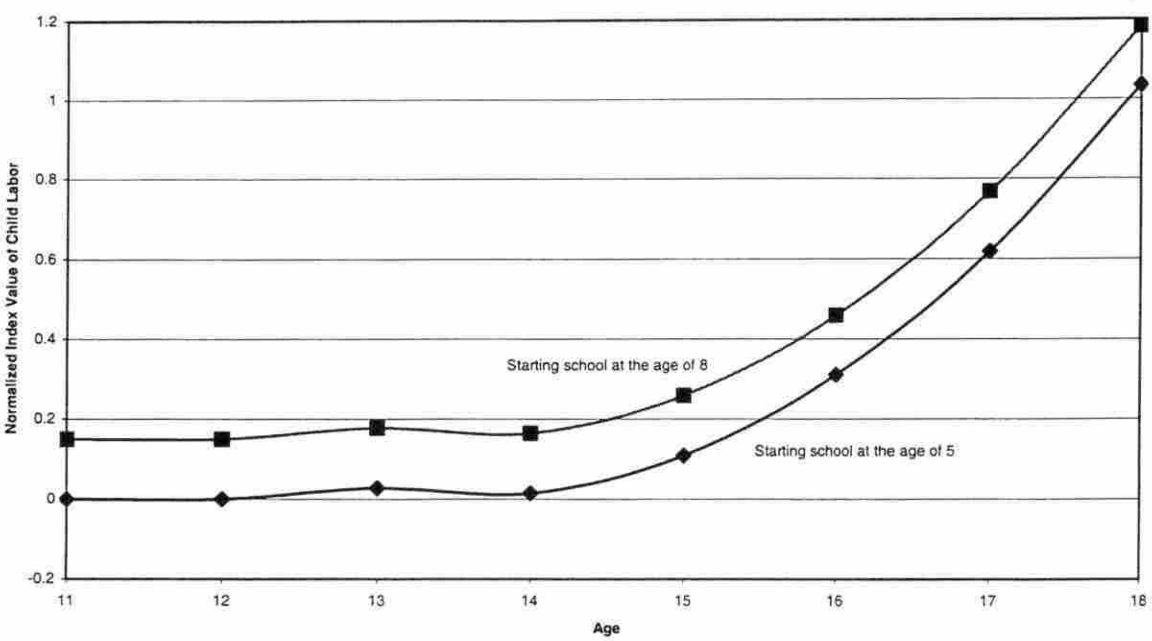

Figure IV.3c The Likelihood of Working and Age with School Start Ages, TIMSS Sample. Based on Predictions Reported in Table IV.5.

Table IV.1a Variable Description Latin America Data.

Endogenous variables	
Math Score	Mathematics test score (C)
Language Score	Language test score (C)
Work Outside	Index of how often student works outside the home (0-2) (C)
Exogenous variables	
Child	
Age	Student age (years) (C)
d10	Dummy if student is below 10 years old
Boy	Dummy if student is a boy (C)
No Preschool	Student did not attend preschool/kindergarten (C)
Parents/Household	
Parent Educ	Average education of parent(s) or guardian(s) (P)
Books at Home	Number of books in student's home (P)
Parents Spanish	Dummy variable indicating if parent's native language is Spanish (Portuguese) (P)
Teacher	
Male	Dummy if teacher is male (T)
Teacher Educ	Aggregated teacher education (T)
School	
Total Enr	Total number of students enrolled at school (Pr)
Spanish Enr	Total number of Spanish (Portuguese) speaking students enrolled (Pr)
Inadequacy	Index of school supply inadequacy (Pr)
Math/week	Number of mathematics classes per week (Pr)
Spanish/week	Number of Spanish (Portuguese) classes per week (Pr)
Community *(Reference:* Metropolitan area with 1M people or more*)*	
Urban	Dummy variable indicating if school is located in an urban area (2,500-1M people) (S)
Rural	Dummy variable indicating if school is located in a rural area (less than 2,500 people) (S)
Instruments	
Legal structure	
Comp Start Age	Compulsory school starting age in the country (U)
Comp End Age	Compulsory school ending age in the country (U)
Preprimary	Dummy variable indicating if the country has a compulsory preprimary school year (U)
Marriage	Percentage of 15-19 year olds married in the country (UN)
Stability	Estimate of political stability 2000/01 (KKL)
Regulation	Estimate of regulatory quality 2000/01 (KKL)
Law	Estimate of rule of law 2000/01 (KKL)

Sources: C: Child survey or test; P: Parent's survey; T: Teacher's survey; Pr: Principle's survey; S: Survey Designer's observation; U: UNESCO estimate (2001); UN: UN (2000); KKL: Estimate taken from Kaufmann, Kray and Lobaton (2002).

Table IV.1b Variable Description TIMSS Data.

Endogenous variables	
Math Score	Test score mathematics (C)
Science Score	Test score science (C)
Work Paid	Index of how often student works at a paid job (1-5) (C)
Exogenous variables	
Child	
Age	Student age (years) (C)
d13	Dummy if student is below 13 years old
Boy	Dummy if student is a boy (C)
Test Language	Frequency of which student speaks test language (1-3) (C)
Parents/Household	
Mother's Educ	Education level of mother (1-6) (C)
Father's Educ	Education level of father (1-6) (C)
Both Parents	Student living with none, one or two parents (0-2) (C)
People Home	Number of people living at home (C)
Books at Home	Index of number of books in student's home (1-5) (C)
Teacher	
Teacher Age	Teacher age (years) (T)
Male	Dummy if teacher is male (T)
Teacher Educ	Aggregated teacher education (T)
School	
Total Enr	Total number of students enrolled at school (Pr)
Girls Enr	Percentage of girls enrolled of total (Pr)
Shortage	Index of school supply shortages (Pr)
Class Size	Average class size (Pr)
Community	
Rural	Dummy if school is located in a rural area (Pr)
Instruments	
Legal structure	
Prim Start	Compulsory primary school starting age in the country (U)
Up Sec Age	Compulsory school ending age of upper secondary education in the country (R)
Marriage	Percentage of 15-19 year olds married in the country (UN)
Stability	Estimate of political stability 2000/01 (KKL)
Regulation	Estimate of regulatory quality 2000/01 (KKL)
Law	Estimate of rule of law 2000/01 (KKL)

Sources: C: Child survey or test; T: Teacher's survey; Pr: Principle's survey, U: UNESCO estimate (2002); R: Right to Education ; UN: UN (2000); KKL: Estimate taken from Kaufmann, Kray and Lobaton (2002).

Table IV.2a Summary Statistics Latin America Data, Mathematics.

Variable	N	Mean	Std. Dev.	Min	Max
Endogenous variables					
Math Score	43861	15.177	6.191	0	32
Work Outside	34172	0.798	0.790	0	2
Exogenous variables					
Child					
Age	31695	9.813	1.533	6	18
d10	31695	0.495	0.500	0	1
Boy	36503	0.503	0.502	0	1
No Preschool	33711	0.238	0.426	0	1
Parents/Household					
Parent Educ	29046	2.702	1.620	0	6
Books at Home	29023	2.373	0.898	1	4
Parents Spanish	23782	0.930	0.255	0	1
Teacher					
Male	33299	0.202	0.401	0	1
Teacher Educ	29767	1.464	0.547	0	2
School					
Total Enr	40531	614.296	581.471	0	6026
Spanish Enr	35825	516.955	553.986	0	6026
Inadequacy	27476	0.341	1.102	-0.925	3.244
Math/week	32178	6.029	2.876	1	30
Community					
Urban	43861	0.469	0.499	0	1
Rural	43861	0.294	0.455	0	1
Instruments					
Legal structure					
Comp Start Age	43861	5.911	0.677	5	7
Comp End Age	43861	13.616	0.997	12	16
Preprimary	43861	0.278	0.448	0	1
Marriage	43861	16.562	5.073	12	29
Stability	43861	-0.054	0.675	-1.361	0.870
Regulation	43861	0.321	0.428	-0.433	1.149
Law	43861	-0.279	0.611	-1.062	1.193
Interaction terms					
Boy*Comp Start Age	36503	2.968	2.990	0	7
Boy*Comp End Age	36503	6.910	6.903	0	16
Boy*Preprimary	36503	0.189	0.631	0	6
Age*(1-d10)	31695	5.533	5.560	0	18
Age^2* (1-d10)	31695	61.518	64.999	0	324
Age*Rural*(1-d10)	31695	2.087	4.413	0	18
Age^2*Rural*(1-d10)	31695	23.831	52.167	0	324
Boy*Rural	36503	0.151	0.358	0	1

Table IV.2b Summary Statistics Latin America Data, Language.

Variable	N	Mean	Std. Dev.	Min	Max
Endogenous variables					
Language Score	44000	11.570	4.370	0	19
Work Outside	35222	0.789	0.789	0	2
Exogenous variables					
Child					
Age	37294	9.712	1.456	6	18
d10	37294	0.784	0.412	0	1
Boy	37610	0.502	0.500	0	1
No Preschool	34784	0.239	0.426	0	1
Parents/Household					
Parent Educ	30000	2.727	1.615	0	6
Books at Home	29986	2.387	0.900	1	4
Parents Spanish	24848	0.933	0.250	0	1
Teacher					
Male	33526	0.201	0.401	0	1
Teacher Educ	29007	1.450	0.545	0	2
School					
Total Enr	40668	609.854	569.433	0	6026
Spanish Enr	36058	513.766	541.697	0	6026
Inadequacy	28034	0.438	1.100	-0.831	3.329
Spanish/week	33312	6.157	3.460	0	30
Community					
Urban	44000	0.471	0.499	0	1
Rural	44000	0.294	0.456	0	1
Instruments					
Legal structure					
Comp Start Age	44000	5.907	0.675	5	7
Comp End Age	44000	13.617	0.996	12	16
Preprimary	44000	0.279	0.448	0	1
Marriage	44000	16.545	5.065	12	29
Stability	44000	0.209	0.648	-0.871	1.363
Regulation	44000	0.321	0.429	-0.433	1.101
Law	44000	-0.277	0.614	-1.064	1.194
Interaction terms					
Boy*Comp Start Age	37610	2.960	2.986	0	7
Boy*Comp End Age	37610	6.884	6.893	0	16
Boy*Preprimary	37610	0.142	0.349	0	1
Age*(1-d10)	37294	2.579	4.940	0	18
Age^2*(1-d10)	37294	31.054	60.860	0	324
Age*Rural*(1-d10)	37294	1.149	3.559	0	18
Age^2*Rural*(1-d10)	37294	13.993	44.280	0	324
Boy*Rural	37610	0.145	0.352	0	1

Table IV.2c Summary Statistics TIMSS Data.

Variable	N	Mean	Std. Dev.	Min	Max
Endogenous variables					
Math Score	69790	480.390	95.348	180.870	795.413
Science Score	69790	487.378	94.929	82.440	806.714
Work Paid	60984	1.555	1.137	1	5
Exogenous variables					
Child					
Age	67317	14.056	0.868	11	18
d13	69794	0.250	0.433	0	1
Boy	69106	0.482	0.503	0	1
Parents/Household					
Mother's Educ	53094	2.916	1.719	1	6
Father's Educ	51348	3.005	1.713	1	6
Both Parents	67643	1.762	0.497	0	2
People Home	66820	5.041	1.863	2	15
Test Language	65496	1.198	0.495	1	3
Books at Home	68336	3.180	1.325	1	5
Teacher					
Teacher Age	54803	3.488	1.138	1	6
Male	54708	0.318	0.466	0	1
Teacher Educ	54493	5.782	1.734	1	8
School					
Total Enr	57745	774.102	593.714	3	3516
Girls Enr	57745	49.460	18.819	0	100
Shortage	64652	8.999	2.939	3.485	13.939
Class Size	56190	29.331	8.948	5.511	60
Community					
Rural	66061	0.331	0.471	0	1
Instruments					
Legal structure					
Prim Start	69794	6.487	0.858	5	8
Up Sec End	69794	14.960	0.747	14	16
Marriage	69794	8.979	5.806	2	22
Stability	69794	0.132	0.561	-1.361	0.754
Regulation	69794	-0.015	0.725	-1.423	0.881
Law	69794	0.079	0.541	-0.874	0.760
Interaction terms					
Boy*Rural	65417	0.160	0.367	0	1
Boy*Prim Start	69106	3.051	3.183	0	7
Boy* Up Sec End	69106	8.838	9.186	0	19
Age*(1-d13)	67317	10.694	6.353	0	18
Age^2*(1-d13)	67317	154.729	93.164	0	324
Age*Rural*(1-d13)	63745	3.707	6.325	0	18
Age^2*Rural*(1-d13)	63745	53.738	92.122	0	324

Table IV.3 Latin America Ordered Probit Regression Results on Child Labor.

Variable	Mathematics	Language
Instruments/Interaction terms		
Boy	0.578*	-0.161
	(0.235)	(0.309)
Rural	0.284*	0.230*
	(0.029)	(0.022)
Boy*Rural	0.013	0.042
	(0.030)	(0.027)
Comp Start Age	-0.512*	0.035
	(0.051)	(0.045)
Comp End Age	-0.061*	-0.006
	(0.012)	(0.011)
Preprimary	-0.572*	0.150*
	(0.059)	(0.069)
Boy*Comp Start Age	-0.004	0.102*
	(0.021)	(0.035)
Boy*Comp End Age	-0.023	-0.019
	(0.013)	(0.013)
Boy*Preprimary	0.014	0.200*
	(0.014)	(0.052)
d10	2.035*	3.166*
	(0.535)	(1.011)
Age*(1-d10)	0.260*	0.444*
	(0.091)	(0.159)
Age^2*(1-d10)	-0.006	-0.013*
	(0.004)	(0.006)
Age*Rural*(1-d10)	0.051*	0.044*
	(0.013)	(0.020)
Age^2*Rural*(1-d10)	-0.005*	-0.004*
	(0.001)	(0.002)
Legal structure		
Political Stability	0.262*	-0.151*
	(0.027)	(0.017)
Regulation	0.264*	0.177*
	(0.036)	(0.035)
Law	-0.537*	-0.090*
	(0.043)	(0.023)
Marriage	0.003	0.008*
	(0.002)	(0.002)
Exogenous variables		
Child		
No Preschool	0.016	0.044*
	(0.017)	(0.016)
Parents/Household		
Parent Educ	-0.077*	-0.072*
	(0.006)	(0.006)

Table IV.3 (Continued)

Variable	Mathematics	Language
Books at Home	-0.064*	-0.064*
	(0.010)	(0.009)
Parents Spanish	-0.106*	-0.158*
	(0.036)	(0.035)
Teacher		
Male	0.059*	0.063*
	(0.020)	(0.018)
Teacher Educ	0.035*	0.054*
	(0.017)	(0.015)
School		
Tot Enr/100	-0.004*	-0.002
	(0.002)	(0.002)
Spanish Enr/100	0.002	0.000
	(0.002)	(0.002)
Inadequacy	0.034*	0.054*
	(0.008)	(0.007)
Math/week (Spanish/week)	-0.008*	-0.004
	(0.003)	(0.002)
LL	-29552.884	-34940.621
Pseudo-R^2	0.046	0.042
N	28939	34306

* indicates significance at the 0.05 confidence level. Standard errors in parentheses. Regressions also include dummy variables controlling for missing values.

Table IV.4 Latin America Least Squares and Instrumental Variables Equations on Test Scores.

	Child Labor Exogenous[a]		Child Labor Endogenous[b]	
Variable	**Mathematics**	**Language**	**Mathematics**	**Language**
Work Outside	-1.254*	-1.032*	-6.961*	-6.818*
	(0.045)	(0.028)	(0.460)	(0.571)
Beta Coefficient[c]	-0.161	-0.189	-0.414	-0.549
Child				
Age	0.061*	0.053*	0.333*	0.401*
	(0.024)	(0.016)	(0.040)	(0.044)
Boy	0.765*	-0.309*	2.213*	1.149*
	(0.068)	(0.043)	(0.148)	(0.171)
No Preschool	-0.496*	-0.310*	-0.361*	-0.062
	(0.084)	(0.053)	(0.109)	(0.104)
Parents/Household				
Parent Educ	0.472*	0.369*	0.063	-0.032
	(0.029)	(0.019)	(0.053)	(0.053)
Books at Home	0.872*	0.541*	0.370*	0.075
	(0.051)	(0.031)	(0.092)	(0.070)
Parents Spanish	0.339	0.658*	-0.650*	-0.469
	(0.178)	(0.118)	(0.276)	(0.248)
Teacher				
Male	-0.424*	-0.448*	0.125	-0.023
	(0.100)	(0.060)	(0.163)	(0.130)
Teacher Educ	-0.551*	0.157*	-0.490*	0.311*
	(0.075)	(0.048)	(0.122)	(0.100)
School				
Total Enr/100	0.090*	0.025*	0.081*	0.026
	(0.009)	(0.007)	(0.014)	(0.014)
Spanish Enr/100	-0.105*	0.004	-0.118*	-0.027
	(0.010)	(0.007)	(0.017)	(0.016)
Inadequacy	-0.410*	-0.326*	-0.057	0.096
	(0.040)	(0.024)	(0.079)	(0.066)
Math/week (Spanish/week)	0.008	0.011	-0.039	-0.021
	(0.014)	(0.007)	(0.022)	(0.016)
Community				
Urban	0.386*	0.078	-0.051	-0.222*
	(0.087)	(0.054)	(0.100)	(0.054)
Rural	-0.838*	-1.137*	0.364*	0.009
	(0.108)	(0.067)	(0.176)	(0.168)
Constant	14.871*	9.408*	-0.491	29.979*
	(0.425)	(0.231)	(4.460)	(6.067)
R^2	0.135	0.174	0.135	0.171
N	28939	34306	28939	34306

[a] Standard errors in parentheses. [b] Bootstrap standard errors in parentheses. * indicates significance at the 0.05 confidence level. [c] The Beta coefficients indicates the number of standard deviation the test score will change from a one standard deviation increase in child labor. Regressions also include dummy variables controlling for missing values.

Table IV.5 TIMSS Ordered Probit Results on Child Labor.

Variable	TIMSS
Instruments/Interaction terms	
Boy	-0.493*
	(0.237)
Rural	0.055
	(0.030)
Boy*Rural	0.026
	(0.025)
Prim Start	0.115*
	(0.016)
Up Sec End	-0.055*
	(0.022)
Boy*Prim Start	-0.135*
	(0.015)
Boy*Up Sec End	0.112*
	(0.017)
d13	-9.949*
	(1.796)
Age*(1-d13)	-1.460*
	(0.239)
Age^2*(1-d13)	0.054*
	(0.008)
Age*Rural*(1-d13)	0.036
	(0.019)
Age^2*Rural*(1-d13)	-0.002
	(0.001)
Legal structure	
Political Stability	-1.075*
	(0.089)
Regulation	-0.361*
	(0.067)
Law	1.621*
	(0.147)
Marriage	0.001
	(0.003)
Exogenous variables	
Parents/Household	
Mother's Educ	-0.007
	(0.006)
Father's Educ	-0.034*
	(0.006)
Test Language	-0.121*
	(0.013)
People Home	0.031*
	(0.004)
Both Parents	-0.123*

Table IV.5 (Continued)

Variable	TIMSS
	(0.012)
Books at Home	-0.052*
	(0.005)
Teacher	
Teacher Age	-0.025*
	(0.006)
Male	0.032*
	(0.015)
Teacher Educ	0.009
	(0.006)
School	
Tot Enr/100	-0.005*
	(0.001)
Girls Enr	-0.003*
	(0.000)
Shortage	0.002
	(0.002)
Class Size	-0.007*
	(0.001)
LL	-45863.150
Pseudo-R^2	0.052
N	56247

* indicates significance at the 0.05 confidence level. Standard errors in parentheses. Regressions also include dummy variables controlling for missing values.

Table IV.6 TIMSS Least Squares and Instrumental Variables Equations on Test Scores.

	Child Labor Exogenous[a]		Child Labor Endogenous[b]	
Variable	**Mathematics**	**Science**	**Mathematics**	**Science**
Work Paid	-5.781*	-5.023*	-27.335*	-36.332*
	(0.326)	(0.333)	(4.263)	(4.499)
Beta Coefficient[c]	-0.068	-0.059	-0.119	-0.159
Child				
Age	6.207*	9.783*	8.617*	13.274*
	(0.428)	(0.437)	(0.740)	(0.704)
Boy	7.479*	18.961*	14.504*	28.880*
	(0.738)	(0.755)	(1.601)	(1.562)
Parents/Household				
Mother's Educ	3.081*	1.397*	2.493*	0.570
	(0.330)	(0.338)	(0.358)	(0.466)
Father's Educ	3.271*	2.946*	2.151*	1.377*
	(0.328)	(0.336)	(0.437)	(0.476)
Test Language	-0.731	-2.983*	-3.372*	-6.688*
	(0.831)	(0.850)	(1.022)	(0.940)
People Home	-5.903*	-5.157*	-5.423*	-4.440*
	(0.223)	(0.228)	(0.265)	(0.261)
Both Parents	8.725*	9.206*	5.237*	4.328*
	(0.740)	(0.756)	(0.992)	(1.232)
Books at Home	16.310*	14.426*	14.918*	12.486*
	(0.321)	(0.328)	(0.466)	(0.408)
Teacher				
Teacher Age	3.093*	2.307*	2.973*	2.105*
	(0.380)	(0.388)	(0.387)	(0.415)
Male	-11.254*	-8.614*	-11.222*	-8.556*
	(0.922)	(0.943)	(0.973)	(1.026)
Teacher Educ	10.599*	9.264*	10.958*	9.755*
	(0.267)	(0.273)	(0.277)	(0.308)
School				
Total Enr	0.009*	-0.003*	0.009*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Girls Enr	0.045	0.025	-0.030	-0.081*
	(0.025)	(0.026)	(0.027)	(0.033)
Shortage	0.023	-0.890*	0.140	-0.723*
	(0.140)	(0.143)	(0.158)	(0.142)
Class Size	0.446*	1.046*	0.551*	1.198*
	(0.052)	(0.053)	(0.056)	(0.064)
Community				
Rural	3.721*	-0.063	8.497*	6.715*
	(0.846)	(0.865)	(1.316)	(1.470)

Table IV.6 (Continued)

Variable	Child Labor Exogenous[a] Mathematics	Science	Child Labor Endogenous[b] Mathematics	Science
Constant	261.925*	227.269*	-60.999	-201.916*
	(7.380)	(7.547)	(65.570)	(91.710)
R^2	0.226	0.184	0.225	0.187
N	56247	56247	56247	56247

[a] Standard errors in parentheses. [b] Bootstrap standard errors in parentheses. * indicates significance at the 0.05 confidence level. [c] The Beta coefficients in indicates the number of standard deviation the test score will change from a one standard deviation increase in child labor. Regressions also include dummy variables controlling for missing values.

Table IV.7 Latin America School Level Regressions on Child Labor.

	OLS[a]		Ordered Probit[b]	
Variable	**Mathematics**	**Language**	**Mathematics**	**Language**
Instruments/Interaction terms				
School Mean Work			1.565*	1.541*
			(0.025)	(0.023)
Boy	0.175	0.018	0.366*	0.114
	(0.111)	(0.143)	(0.181)	(0.235)
Boy*Rural	-0.001	0.001	-0.014	-0.005
	(0.016)	(0.014)	(0.026)	(0.022)
Boy*Comp Start Age	0.013	0.037*	0.016	0.056*
	(0.011)	(0.017)	(0.017)	(0.028)
Boy*Comp Start End	-0.008	-0.008	-0.017	-0.017
	(0.006)	(0.006)	(0.009)	(0.009)
Boy*Preprimary	0.016	0.064*	0.027	0.108*
	(0.008)	(0.025)	(0.014)	(0.040)
d10	0.646	1.668*	1.076*	2.638*
	(0.338)	(0.646)	(0.540)	(1.022)
Age*(1-d10)	0.077	0.232*	0.128	0.366*
	(0.057)	(0.102)	(0.091)	(0.161)
Age^2*(1-d10)	-0.002	-0.007	-0.003	-0.012
	(0.002)	(0.004)	(0.004)	(0.006)
Age*Rural*(1-d10)	0.008	0.020	0.017	0.034
	(0.008)	(0.012)	(0.013)	(0.020)
Age^2*Rural*(1-d10)	-0.001	-0.002	-0.002	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)
Exogenous variables				
Child				
No Preschool	-0.016	-0.008	-0.023	-0.009
	(0.010)	(0.010)	(0.017)	(0.016)
Parents/Household				
Parent Educ	-0.012*	-0.010*	-0.025*	-0.022*
	(0.004)	(0.003)	(0.006)	(0.006)
Books at Home	-0.009	-0.010	-0.022*	-0.024*
	(0.006)	(0.006)	(0.010)	(0.009)
Parents Spanish	-0.001	-0.002	0.003	0.001
	(0.022)	(0.021)	(0.035)	(0.034)
Teacher				
Male	-0.006	-0.006	-0.009	-0.002
	(0.012)	(0.011)	(0.020)	(0.018)
Teacher Educ	0.005	0.009	0.012	0.019
	(0.009)	(0.009)	(0.015)	(0.014)
Constant	-0.651	-1.704*		
	(0.340)	(0.647)		

Table IV.7 (Continued)

	OLS[a]		Ordered Probit[b]	
Variable	**Mathematics**	**Language**	**Mathematics**	**Language**
LL			-27880.457	-33030.102
R^2	0.014	0.014		
Pseudo-R^2			0.100	0.094
N	28939	34306	28939	34306

[a] The dependent variable is the deviation of student's work from the school work average. [b] The dependent variable is the individual student's work. * indicated significance at the 0.05 confidence level. Standard errors in parentheses. Regressions also include dummy variables controlling for missing values.

Table IV.8 Latin America School Level Least Squares and Instrumental Variables Regressions on Test Scores.

	Child Labor Exogenous[ab]		Child Labor Endogenous[cb]		Child Labor Endogenous[cd]	
Variable	**Mathematics**	**Language**	**Mathematics**	**Language**	**Mathematics**	**Language**
Work Outside	-0.729*	-0.716*	-11.419*	-7.760*	-11.476*	-7.734*
	(0.039)	(0.026)	(1.962)	(2.174)	(1.497)	(2.410)
Beta Coefficient[e]	-0.110	-0.148	-0.202	-0.187	-0.156	-0.150
School Score Mean					0.973*	0.953*
					(0.009)	(0.007)
Child						
Boy	0.501*	-0.357*	2.060*	0.674*	2.074*	0.671
	(0.056)	(0.037)	(0.294)	(0.318)	(0.245)	(0.354)
Age	0.222*	0.202*	0.287*	0.292*	0.282*	0.282*
	(0.019)	(0.013)	(0.033)	(0.034)	(0.036)	(0.039)
No Preschool	-0.117	-0.156*	-0.280*	-0.206*	-0.298*	-0.223*
	(0.068)	(0.046)	(0.133)	(0.081)	(0.116)	(0.081)
Parents/Household						
Parent Educ	0.147*	0.111*	0.030	0.045	0.041	0.063
	(0.024)	(0.016)	(0.048)	(0.037)	(0.047)	(0.035)
Books at Home	0.317*	0.190*	0.218*	0.120*	0.239*	0.146*
	(0.042)	(0.027)	(0.069)	(0.048)	(0.073)	(0.047)
Parents Spanish	-0.083	0.091	-0.017	0.126	0.003	0.179
	(0.143)	(0.101)	(0.245)	(0.167)	(0.227)	(0.197)
Teacher						
Male	0.071	-0.024	-0.030	-0.092	-0.059	-0.132
	(0.080)	(0.051)	(0.154)	(0.089)	(0.137)	(0.083)
Teacher Educ	-0.066	0.089*	-0.032	0.127	-0.049	0.131
	(0.060)	(0.041)	(0.099)	(0.074)	(0.117)	(0.071)
Constant	-3.194*	-2.548*	-4.103*	-3.673*	-3.717*	-3.188*
	(0.274)	(0.190)	(0.492)	(0.464)	(0.480)	(0.485)
R^2	0.025	0.039	0.018	0.019	0.419	0.366
N	28939	34306	28939	34306	28939	34306

[a] Standard errors in parentheses. [b] The dependent variable is the deviation of student's test score from the school mean score. [c] Bootstrap standard errors in parentheses. [d] The dependent variable is the student's test score and the predicted child labor used is that reported in Table IV.7 column 3 and 4. * indicates significance at the 0.05 confidence level. [e] The Beta coefficients in indicates the number of standard deviation the test score will change from a one standard deviation increase in child labor. Regressions also include dummy variables controlling for missing values.

Table IV.9 TIMSS School Level Regressions on Child Labor.

Variable	OLS[a]	Ordered Probit[b]
Instruments/Interaction terms		
School Mean Work		1.049*
		(0.015)
Boy	-0.145	-0.231
	(0.129)	(0.174)
Boy*Rural	-0.008	-0.088*
	(0.017)	(0.023)
Boy*Prim Start	-0.008	0.014
	(0.009)	(0.011)
Boy*Up Sec End	0.025*	0.029*
	(0.009)	(0.013)
d13	-1.403	4.061*
	(1.478)	(1.861)
Age*(1-d13)	-0.262	0.457
	(0.197)	(0.248)
Age^2*(1-d13)	0.012	-0.012
	(0.007)	(0.008)
Age*Rural*(1-d13)	0.024	0.061*
	(0.015)	(0.019)
Age^2*Rural*(1-d13)	-0.002	-0.004*
	(0.001)	(0.001)
Exogenous variables		
Parents/Household		
Mother's Educ	0.005	-0.001
	(0.004)	(0.006)
Father's Educ	-0.006	-0.022*
	(0.004)	(0.006)
Books at Home	-0.003	-0.024*
	(0.004)	(0.005)
Test Language	-0.013	-0.057*
	(0.010)	(0.012)
People at Home	0.018*	0.013*
	(0.003)	(0.004)
Both Parents	-0.038*	-0.096*
	(0.009)	(0.012)
Teacher		
Teacher Age	0.009*	0.025*
	(0.005)	(0.006)
Male	-0.047*	-0.057*
	(0.011)	(0.015)
Teacher Educ	0.008*	0.028*
	(0.003)	(0.004)

Table IV.9 (Continued)

Variable	**OLS**[a]	**Ordered Probit**[b]
Constant	1.154	
	(1.478)	
LL		-43835.165
R^2	0.014	
Pseudo-R^2		0.094
N	56247	56247

[a] The dependent variable is the deviation of student's work from the school work average.
[b] The dependent variable is the individual student's work. * indicated significance at the 0.05 confidence level. Standard errors in parentheses. Regressions also include dummy variables controlling for missing values.

Table IV.10 TIMSS School Level Least Squares and Instrumental Variables Regressions on Test Scores.

	Child Labor Exogenous[ab]		Child Labor Endogenous[cb]		Child Labor Endogenous[cd]	
Variable	**Mathematics**	**Science**	**Mathematics**	**Science**	**Mathematics**	**Science**
Work Paid	-4.610*	-3.681*	-176.805*	-198.933*	-196.517*	-206.698*
	(0.292)	(0.299)	(37.301)	(46.530)	(37.502)	(54.872)
Beta Coefficient[e]	-0.065	-0.051	-0.292	-0.319	-0.248	-0.262
School Score Mean					0.887*	0.907*
					(0.007)	(0.007)
Child						
Boy	7.605*	11.242*	38.085*	52.101*	41.608*	53.659*
	(0.361)	(0.369)	(7.129)	(8.871)	(6.622)	(10.202)
Age	6.689*	16.502*	17.589*	22.565*	18.580*	22.901*
	(0.602)	(0.616)	(2.235)	(2.761)	(2.268)	(3.380)
Parents/Household						
Mother's Educ	1.998*	1.630*	2.963*	2.725*	3.163*	2.676*
	(0.276)	(0.282)	(0.607)	(0.729)	(0.696)	(0.707)
Father's Educ	1.574*	1.727*	0.557	0.573	0.652*	0.646
	(0.277)	(0.283)	(0.621)	(0.770)	(0.675)	(0.712)
Books at Home	6.995*	6.367*	6.474*	5.776*	7.528*	6.547
	(0.267)	(0.273)	(0.743)	(0.639)	(0.678)	(0.685)
Test Language	-0.293	0.526	-2.382	-1.843	-2.562	-2.199
	(0.693)	(0.709)	(1.956)	(1.712)	(2.148)	(2.279)
People at Home	-0.083	-0.596*	3.241*	3.173*	2.921*	2.896*
	(0.186)	(0.190)	(0.948)	(1.022)	(0.892)	(1.146)
Both Parents	0.993	0.177	-5.549*	-7.241*	-5.358*	-6.601*
	(0.625)	(0.639)	(2.364)	(2.588)	(2.499)	(2.961)
Teacher						
Teacher Age	-1.668*	-1.619*	-0.003	0.269	0.713	0.711
	(0.315)	(0.322)	(0.675)	(0.957)	(0.852)	(0.966)
Male	2.488*	1.809*	-5.569*	-7.327*	-8.035*	-8.628*
	(0.755)	(0.772)	(2.058)	(3.028)	(2.654)	(3.091)
Teacher Educ	-1.907*	-1.872*	-0.395	-0.158	1.007	0.763
	(0.206)	(0.211)	(0.639)	(0.611)	(0.592)	(0.741)
Constant	-119.538*	-168.4198	-296.626*	-369.255*	-270.748	-338.032*
	(5.870)	(6.002)	(40.137)	(48.042)	(39.639)	(59.109)
R^2	0.052	0.051	0.063	0.064	0.447	0.417
N	56247	56247	56247	56247	56247	56247

[a] Standard errors in parentheses. [b] The dependent variable is the deviation of student's test score from the school mean score. [c] Bootstrap standard errors in parentheses. [d] The dependent variable is the student's test score and the predicted child labor used is that reported in Table IV.9 column 2. * indicates significance at the 0.05 confidence level. [e] The Beta coefficients indicate the number of standard deviation the test score will change from a one standard deviation increase in child labor. Regressions also include dummy variables controlling for missing values.

Table IV.11 Latin America Ordered Probit Results on Child Labor, Community Details.

Variable	Mathematics	Language
Instruments/Interaction terms		
Boy	0.644*	-0.150
	(0.245)	(0.317)
Comp Start Age	-0.532*	-0.010
	(0.054)	(0.048)
Comp End Age	-0.072*	-0.013
	(0.012)	(0.011)
Preprimary	-0.601*	0.080
	(0.062)	(0.074)
Boy*Comp Start Age	-0.004	0.112*
	(0.023)	(0.036)
Boy*Comp End Age	-0.027*	-0.024
	(0.013)	(0.013)
Boy*Preprimary	0.018	0.230*
	(0.017)	(0.054)
d10	1.858*	3.013*
	(0.555)	(1.063)
Age*(1-d10)	0.257*	0.438*
	(0.093)	(0.166)
Age^2*(1-d10)	-0.008*	-0.014*
	(0.004)	(0.006)
Capital Developed	-0.437*	-0.427*
	(0.044)	(0.042)
Capital Marginal	-0.239*	-0.220*
	(0.052)	(0.049)
City Developed	-0.296*	-0.309*
	(0.044)	(0.042)
City Marginal	-0.188*	-0.176*
	(0.048)	(0.047)
Town	-0.120*	-0.135*
	(0.043)	(0.042)
Village	0.061	0.007
	(0.046)	(0.044)
Rural Area	-0.027	-0.008
	(0.042)	(0.042)
Legal structure		
Political Stability	0.247*	-0.145*
	(0.029)	(0.018)
Regulation	0.287*	0.177*
	(0.039)	(0.037)
Law	-0.543*	-0.105*
	(0.045)	(0.025)
Marriage	0.005	0.009
	(0.003)	(0.002)

Table IV.11 (Continued)

Variable	**Mathematics**	**Language**
Exogenous variables		
Child		
No Preschool	0.012	0.037*
	(0.017)	(0.016)
Parents/Household		
Parent Educ	-0.068*	-0.061*
	(0.006)	(0.006)
Books at Home	-0.060*	-0.059*
	(0.011)	(0.010)
Parents Spanish	-0.147*	-0.191*
	(0.038)	(0.037)
Teacher		
Male	0.054*	0.040*
	(0.021)	(0.018)
Teacher Educ	0.054*	0.063*
	(0.017)	(0.016)
School		
Tot Enr/100	0.000	0.002
	(0.002)	(0.002)
Spanish Enr/100	0.002	0.000
	(0.002)	(0.002)
Inadequacy	0.019*	0.042*
	(0.009)	(0.008)
Math/week (Spanish/week)	-0.007*	-0.004
	(0.003)	(0.002)
LL	-27067.016	-31714.564
Pseudo-R^2	0.050	0.046
N	26639	31321

* indicates significance at the 0.05 confidence level. Standard errors in parentheses.
Regressions also include dummy variables controlling for missing values.

Table IV.12 Latin America Least Squares and Instrumental Variables Equations on Test Scores, After Community Detail.

	Child Labor Exogenous[a]		Child Labor Endogenous[b]	
Variable	**Mathematics**	**Language**	**Mathematics**	**Language**
Work Outside	-1.311*	-1.095*	-5.640*	-5.442*
	(0.046)	(0.029)	(0.305)	(0.272)
Beta Coefficient[c]	-0.168	-0.349	-0.336	-0.462
Child				
Age	0.075*	0.042*	0.325*	0.351*
	(0.026)	(0.017)	(0.039)	(0.031)
Boy	0.797*	-0.296*	1.955*	0.860*
	(0.071)	(0.045)	(0.112)	(0.097)
No Preschool	-0.535*	-0.320*	-0.343*	-0.057
	(0.088)	(0.056)	(0.127)	(0.085)
Parents/Household				
Parent Educ	0.513*	0.390*	0.165*	0.053
	(0.031)	(0.019)	(0.050)	(0.039)
Books at Home	0.922*	0.634*	0.437*	0.196*
	(0.054)	(0.033)	(0.071)	(0.061)
Parents Spanish	0.754*	0.926*	-0.425	-0.340
	(0.186)	(0.124)	(0.256)	(0.216)
Teacher				
Male	-0.658*	-0.564*	-0.081	-0.145
	(0.103)	(0.063)	(0.146)	(0.106)
Teacher Educ	-0.571*	0.193*	-0.446*	0.330*
	(0.078)	(0.050)	(0.115)	(0.088)
School				
Total Enr/100	0.111*	0.054*	0.086*	0.039*
	(0.009)	(0.007)	(0.013)	(0.011)
Spanish Enr/100	-0.106*	0.004	-0.119*	-0.020
	(0.011)	(0.007)	(0.013)	(0.012)
Inadequacy	-0.413*	-0.361*	-0.132*	-0.021
	(0.042)	(0.025)	(0.062)	(0.046)
Math/week (Spanish/week)	0.022	-0.001	-0.024	-0.027*
	(0.015)	(0.008)	(0.021)	(0.013)
Constant	13.981*	8.650*	-2.389	21.123*
	(0.441)	(0.240)	(3.363)	(5.994)
R^2	0.131	0.164	0.136	0.172
N	26639	31321	26639	31321

[a] Standard errors in parentheses. [b] Bootstrap standard errors in parentheses. [c] The Beta coefficients indicate the number of standard deviation the test score will change from a one standard deviation increase in child labor. * indicates significance at the 0.05 confidence level. Regressions also include dummy variables controlling for missing values.

Chapter V. Child Labor Research: A Review of Methods and Procedures

Extracted parts from "Child Labor, School Attendance and Academic Performance: A Review." Working paper.

Peter F. Orazem and Victoria Gunnarsson

V.I. Introduction

In order to successfully plan and conduct research in the field of child labor and schooling outcomes it is important to understand the mechanics behind the relationship between children's work and human capital production in schools and what type of data to collect to best obtain the desired results.

In this paper we outline the methodological issues to consider when studying the impact of the intensity of children's work on educational outcomes, the most important variables to use, different estimation techniques, appropriate sampling methods and discuss the most prominent gaps in the research record thus far. The literature review in Chapters III and IV is extended to address issues like birth order effects and income transfer programs and finally we attempt to identify potential data sources which could be used to address existing gaps in the research record.

In addition, we make use of one of two unique data sets that include data on both child labor and test scores to evaluate the effect of numbers of hours worked on academic achievement. Our results suggest that as daily number of hours of work increase, the adverse effects on test scores increase and it is evident that modeling market work endogenously instead of exogenously corrects for the upward bias in test scores predicted by the exogenous model.

V.II. Theory of Child Labor and School Attendance

Children specialize in schooling early in life. Eventually, they leave school and enter the labor market full-time, whether as children or adults. Many will experience an intermediate period in which they devote some time to work while still in school. It is useful to lay out the economic rationale for this pattern of time allocation as the child ages in order to highlight the variables that should be incorporated in empirical studies of child labor and school achievement.

A simple three-stage variant of the Ben-Porath (1967) model can be used to outline the exogenous and endogenous variables that enter the time allocation decision. This model is not meant to characterize all the complications of the school and work decisions concerning the child, but merely to indicate which variables we need to consider in characterizing those decisions.

We assume that the parents decide how to allocate child time between labor, L, and school attendance, A, so as to maximize the present value of the child's lifetime earnings.[1] We assume initially that households do not face any constraints on borrowing against future returns to schooling, an assumption that will be relaxed later. In each period, the time constraint is given by $A + L = 1$, so we ignore the decision on child leisure. Furthermore, assume that there are positive returns to schooling, and that eventually, returns to an additional year of schooling decreases as years of schooling rises.[2] These assumptions are sufficient to predict that a child will decrease time in school as the child ages.[3] These assumptions are sufficient to predict that a child will decrease time in school as the child ages.

The first stage is defined as the length of time the child spends full time in school, so attendance, $A = 1$. In the second stage, $0 < A < 1$, meaning the child divides time between school and work. In the third stage, the child specializes in working, setting $A = 0$. The length of stage one or stage two varies with the parents' assessment of the value of current child labor versus the present value of increased human capital from spending time in school.[4]

The wage the child can claim at time t is $W(H_t)$, where H_t is total marketable skills accumulated up to time t. Between any two periods t = 0 and t = 1, the decision of whether the child attends school will reflect the relative returns to schooling versus working. Let r be the interest rate. If the child attends school so $A > 0$, s/he will earn $(1 - A)\ W(H_0)$ in the current period, but the wage will rise to $W(H_1) = W(H(H_0, A))$ in the next period. Human capital production depends positively on past human capital accumulation and attendance. If the child does not attend school, $A = 0$ and the child's value of time in both periods is $W(H_0)$.

The child will attend school if

$$(1-A)W(H_0)+\frac{W(H_1)}{1+r} \geq W(H_0)+\frac{W(H_0)}{1+r}$$

or (V.1)

$$-AW(H_0)+\frac{W(H_1)-W(H_0)}{1+r} \geq 0$$

Condition (V.1) says that the child should attend if the present value of the wage increase attributable to schooling exceeds the cost of child time in school. If condition (V.1) holds with inequality, A will be set equal to one and the child will spend the period in stage one. If the condition holds with equality, optimal attendance will be in stage two where $0 < A < 1$. If the condition is violated, then the child will be in stage three where $A = 0$.

Because returns to human capital are positive but diminishing as the level of human capital increases, the first term on the left-hand-side of (V.1) grows progressively larger in magnitude and the second term on the left-hand-side becomes progressively smaller as the child ages. Consequently, the child's schooling pattern will go from full-time schooling $(A = 1)$; to part-time schooling $(0 < A < 1)$; to leaving school $(A = 0)$ as the child gets older. The pattern is illustrated in Figure V.1. A child's age is an important exogenous variable explaining the amount of time the child will spend in school.

Rarely will we have longitudinal data on children that would allow us to follow a child's time in school over time. More typically, we will have a cross section of children of the same age. Nevertheless, in most developing countries, these children will be in different schooling stages, even at very young ages. Variation across households in the strength of the local labor market for children, past human capital accumulation, the quality of schools, household income, and borrowing costs or credit constraints can all be shown to explain variation in child time in school or work, even in this very simple model.

i) Child labor market: The strength of the market for child labor can be measured by the local market wage for children, $W(H_0)$. Child wages would be expected to vary by age, by sex, and by the rural nature of the community. If information on child wages is not available, one can use information on age, sex and rural nature of the community as good proxies. Higher order combinations of these variables may serve as suitable instruments for child labor in the absence of good wage information. An increase in the child wage rate without a corresponding increase in anticipated future wages would shift the attendance schedule to the left as in Figure V.2.[5] Children would move into stages two and three at younger ages.

ii) Past accumulations of human capital: Current human capital accumulation has an ambiguous effect on attendance stage because it can raise both current wages and school productivity. However, if the child wage is dependent more on a child's physical stature than the child's schooling attainment, higher acquired human capital would shift the attendance schedule in Figure V.1 to the right. Past accumulations of human capital are typically measured by school attainment. However, an important component of past accumulations of human capital is unmeasured ability. More able children will succeed more readily in school, but the unmeasured ability may also have an impact on child labor status. As we will demonstrate formally in the next section, missing information on ability endowment can bias the estimated relationship between child labor and school achievement if, for example, children with smaller ability endowments have lower test scores but are also more likely to work. Partial controls for this missing ability endowment may include the use of IQ tests such as the Raven's score or by the inclusion on information on the parents' human capital. However, the problem of ability bias is unlikely to be convincingly resolved with only cross sectional data. The conclusion from numerous studies of the impact of ability bias on estimated returns to schooling has concluded that the bias is small (Card, 1999). While of some comfort, there is no guarantee that the bias from missing ability on estimates of the impact of child labor on achievement would also be small.

iii) <u>School quality</u>: Better schools will raise the anticipated increase in human capital from an additional year of schooling. As a consequence, an improvement in school quality will shift the attendance schedule to the right if child wages are driven by stature rather than school achievement. In cross sections, we would expect a higher incidence of child labor in places with weaker schools. Therefore, as with ability endowments, properly measuring the impact of child labor on school achievement must control for the quality of local schools.

iv) <u>Household Nonlabor Income, Farm Assets and Credit Constraints:</u> Nonlabor income will alter condition (V.1) for two reasons.[6] First, income may make schooling more productive so that $W(H_1) - W(H_0)$ rises as household income increases.[7] The impact of an adverse income shock is illustrated in Figure V.2. If the income loss lowers schooling productivity, the attendance schedule shifts to the left, causing children aged t_0 to t_1 to enter the labor market that would otherwise be full-time in school. The shock would also induce children aged t_2 to t_3 to drop out of school that would otherwise attend part time. A large enough income shock could cause children in stage one to move all the way to stage three.

Earlier, we assumed there were no credit constraints, but that is unlikely to be true in the case of human capital investments. For any number of reasons (that human capital does not have collateral value, that lenders cannot coerce repayment on educational investments, that returns to human capital are too risky, or that parents cannot insure that their children will repay schooling investments) investments in human capital are likely to be credit constrained, particularly for poor households.

Liquidity constraints can be characterized as a circumstance by which interest rates increase as household income falls. If true, then poor households discount returns to schooling more heavily, the left-hand-side of equation (V.1) becomes more negative, and their children enter stages two and three at younger ages. Information on loan rates is not easily obtained, but measures of household wealth or collateral, poverty or income may serve as suitable proxies. Preference would be for wealth measures that are less subject to endogenous labor supply decisions.

Most children who work are engaged in household enterprise activities, whether it be a farm, a home-based manufacturing operation, or a retail enterprise. These productive assets would have mixed impacts on child labor. On the one hand, they may raise a child's opportunity cost of time in school because the child is productive in labor activities. On the other hand, adults in the household are also more productive, so the household can better afford allocating child time to schooling activities. This explains why some studies of agricultural households have found that measures of the farm capital stock lower child labor (Levy, 1985) while others find the opposite (Rosenzweig and Evenson, 1977; Cockburn, 2000).

iv) <u>Number of members in the household and birth order effects</u>: Holding household wealth or parental human capital constant, larger households have fewer resources per capita. Thus, we might anticipate household size to be an alternative measure of poverty. This is not quite accurate, however. More adults per household would raise the earnings potential of the household. Thus, demographic information on the number of adults and children in the household would be important. Similarly, younger children may benefit from the presence of working older children in poor households. These birth order effects on schooling investments have been discussed, but few empirical analyses exist. Nevertheless, it may be important to know not just the number of siblings a child has, but where the child stands in the order of births.

V.III. The Value Added Approach

The theory of child labor and human capital production in schools was laid out in section IV.IV of Chapter IV. The compounding problem in estimating the test scores equation, (IV.3), is the presence of past human capital accumulations, *X*. Child labor is a function of *X*, so direct estimation of (IV.3) will be biased due to correlation between the error term which includes *X* and *CL*. Even if *CL* is identified by instruments, estimation of (IV.3) may be biased by correlation between *X* and other child specific, household, teacher, school and community variables. This has led to the use of so-called "value added" specifications where past test scores are used as proxies for *X*. In those studies, the dependent variable is measured by $Q - X$, so only the gain in human capital in the current schooling period is used as the dependent variable.

To our knowledge, the few data sets that include both measures of child labor and test scores do not have two temporally distant test scores to allow the value added specification to be estimated. In addition, few studies have tried to correct for the likely endogeneity of child labor.

In a single cross sectional data set, the absence of a test score in the base period may be finessed somewhat. First, if the children are all in the same grade, the children must have established at least a threshold level of human capital that qualified the child to be promoted from the past grade level. Second, if the children are at relatively early stages of their schooling, variation across children in X may be small simply because they have not learned much yet. Finally, inclusion of other variables that may be viewed as highly correlated with X such as parental education, sibling attributes, Raven's scores or other IQ measures, or other variables which are believed to reflect human capital endowments may be sufficient to control for the missing measure of X. Nevertheless, it should be noted that any of these fixes leaves the potential that the coefficients will still be biased if these proxies do not sufficiently control for the missing measure of human capital endowment.

The general empirical strategy suggested by this discussion is to collect variables that shift the probability of child labor in equation (IV.2) but do not enter the educational production function (IV.3). In designing a new sample, effort should also be taken to establish a measure of X if at all possible.

V.IV. Variable Definitions

Empirical tests of the theoretical model outlined in the previous two sections and in section IV.IV require data on child time allocations, household, school and community attributes, measures of the value of child time, and measures of schooling outcomes. This section discusses alternative empirical measures for these theoretical variables.

V.IV.I Child Labor

LOCATION: Child labor generally takes on two forms: unpaid work in the household or in a household farm or enterprise, and outside work in the paid labor market. Most child labor is unpaid and conducted in family-owned enterprises, making it difficult to distinguish from household chores. Nevertheless, the adverse consequences of child labor may differ by whether they are oriented toward market or home production, as well as whether they are inside or outside the home. Consequently, questions need to define child time allocation to work activities by where they occur (inside or outside the household) and whether or not they are related to a family enterprise.

GENDER: Another reason to monitor work in the home as well as work outside the home is that girls are more likely to work inside the home while boys are more likely to work outside the home. Concentrating solely on work outside the home may understate the amount of time girls devote to work. Absent strong evidence of the relative adverse consequences of one type of work relative to the other, information on both should be collected.

INTENSITY: The potential damage that can be done by child labor also depends on its intensity. Working one or two hours per day may not interfere with schooling, may not make the child too tired to perform, and may even generate sufficient resources to enable the household to afford to send the child to school. Therefore, it is important to know how many hours a child works per day.

LENGTH OF SPELL: Child labor may be continuous over the year or may be subject to short spells. These spells may be related to seasonal demand for child labor, say from need for additional labor at planting or harvest, or due to transitory shocks to household income. A recent study by Duryea et al. (2003) found that the average length of a spell of child labor in urban areas of Brazil was about four months. Jacoby and Skoufias (1997) found that rural households in India used child labor to help insulate the household from adverse shocks to household income. While these transitory spells of child labor may disrupt a child's education, the disruption is presumably less severe than if the child labor is continuous. This suggests that questions regarding child labor should establish how regularly the child works as well as whether or not the child works.

The adverse consequences of child labor are likely to accumulate over time. In any single cross sectional survey, two children with similar current child labor status may have had very different child labor histories. Retrospective questions on past accumulations of child labor can capture long-term versus contemporaneous incidence of child labor.

HAZARDOUS CHILD LABOR: Child labor may also have differential consequences by the type of work conducted. The International Labour Organization's Convention No. 182 advocates the prohibition and elimination of the worst forms of child labor, where the worst forms include the types of child labor that harm child health, safety and moral development.[8] Graitcer and Lerer (1998) provide a comprehensive international review of the state of knowledge of the impact of child labor on health. Data on the extent of child labor itself is subject to considerable error, but data on the incidence of child injuries on the job are even more problematic. Sources of information come from government surveillance, sometimes supplemented by data from worker's compensation or occupational health and safety incidence reports. These latter sources are less likely to be present in the informal labor markets in which child labor is most common, and government surveillance is often weak. Consequently, Graitcer and Lerer conclude that published epidemiological studies of the health consequences of child labor almost certainly underestimate the incidence of injuries. Nevertheless, the rates are not small. Of working children aged 10-14, nine percent are estimated to suffer injuries annually, and 3.4 percent are estimated to suffer disabling injuries. Information on longer term health consequences of child labor such as occupational disease or repetitive injuries is even more limited and subject to errors.

Because the incidence of serious injuries is small in any given year, information on injuries needs to be collected on a large number of working children to get accurate rates. If the interest is in establishing injury rates by occupation, the sample needs to be even larger to get accurate rates by occupation. It is preferable to collect this information from household surveys rather than from formal sector data sources (worker's compensation, mandatory employer disclosure) because most child labor is in the informal sector. Furthermore, we really do not have a good information base on actual risky occupations, so limiting the analysis to specific occupations may miss some dangerous jobs. One way to finesse the sample size problem is to ask retrospective information on injuries over several years. While the retrospective information may be subject to error, it is likely that respondents will remember serious injuries.

CHILD REPORTED OR ADULT REPORTED INFORMATION: Several data sets rely on children themselves to report on whether and how much they work. Others rely on a parent or adult to respond on the question. It is not obvious which option is preferable. If the survey design is school based, interviewers may ask children about their parents, their household's attributes and their time allocations. If this information can be obtained from the child, the expense of visiting each household is avoided. However, children may provide less reliable information on child labor, particularly on retrospective data. Responses of the youngest children are likely subject to the greatest measurement error.

V.IV.II Time in School

ENROLLMENT AND ATTENDANCE: Most of the studies that evaluate the impact of child labor on time in school concentrate on whether or not the child is enrolled. In many countries, enrollment rates for working children do not differ dramatically from those of children who are not working, particularly at younger ages. Some have pointed to this evidence as suggesting that child labor and schooling are not mutually exclusive (Ravallion and Wodon, 2000). Less is known about the relationship between child labor and school attendance because it is more difficult to elicit information on school attendance from household surveys. Parents' impressions of their child's attendance record are likely fraught with error. It is possible to integrate official attendance records from the school with household survey data, but this has not been done frequently in practice.[9]

LENGTH OF SCHOOL DAY AND TERM: Longer school days may influence the amount a child can learn. However, longer school days also may influence child labor. The longer the school session, the less time a child has to work. Yap et al. (2003) found that the imposition of an after school program in rural Brazil resulted in a large reduction in the probability of child labor. Length of term also can affect the amount a child learns in a school year. Differences in the length of school term between black and white schools in the United States in the segregated era have been shown to explain differences in school achievement (Orazem, 1987) and earnings (Card and Krueger, 1992) between blacks and whites.

In practice, school terms and school days are often standardized within countries, so they do not prove useful in single country studies. They may help to explain variation in child labor across countries however.

V.IV.III School Outcomes

Time spent in school is a degree removed from actual school outcomes. For example, it is possible that child labor does not alter school enrollment, or even that it does not alter school attendance, but it could still adversely affect school outcomes. Child labor could limit time spent on homework, or it could leave the child too tired to make efficient use of the time on school. Numerous studies of earnings tell us that it is cognitive achievement or highest grade attained that matter for earnings, not time spent in school per se.

HIGHEST GRADE ATTAINED: Years of schooling completed is a commonly used measure in studies if earnings. It is best used as a measure when the target sample is older and beyond schooling age. Therefore, it is the appropriate measure of schooling for parents and adults.

GRADE-FOR-AGE: When the target sample is younger and still in school, a more appropriate measure is schooling attainment relative to the child's age. This also allows for variation in measures of schooling success even within samples based on the same grade as the most successful students are those who attained the given grade at the youngest age.

PROMOTION: Variation in promotion across schools may reflect differences in standards of success, but variation in promotion within a given school should reflect differences in cognitive achievement across children. In practice, it is difficult to use promotion information unless one follows a cohort of students over time. Retrospective promotions collected from a given class will invariably only include those who were promoted to the current grade. Therefore, grade-for-age dominates information on promotions for a single cross-section.

DROPOUT AND CONTINUATION: If one is following a cohort of students over time, one can also distinguish dropouts from students who continue on in school. Dropouts reflect both the child's performance and the parents' schooling demand response to the child's performance in school. Consequently, dropouts are less informative about actual success in school than are promotions. Nevertheless, as the model in section V.II demonstrates, the choice to continue in school is related to the child labor market, school quality and past accumulations of human capital and can be analyzed in its own as an element of schooling choices.[10]

TEST SCORES: In the end, it is cognitive achievement and not time in school that policy-makers are targeting. In fact, in the few studies that have included both measures, it is measures of cognitive achievement and not years of schooling that are important in explaining variation in adult earnings (Glewwe, 2002). Therefore, if we are to measure the adverse consequences of child labor on a child's human capital development, we must use some measure of cognitive attainment.

TEST ADMINISTRATION: Practicality dictates that the tests be administered in a classroom setting. This is not only less costly, but reduces random variability in the outcomes attributable to variation in how the test is administered. Consequently, surveys incorporating test scores will almost certainly be designed around cluster samples of schools. This is even more true if the survey calls for the inclusion of school quality measures, which is almost certain to be the case.

TEST DESIGN: The tests need to be standardized across schools to allow comparisons across children in different labor markets. The tests may also need to be standardized across countries if the study is aimed at explaining differences in human capital production across countries with differing child labor supply patterns. Nevertheless, the tests must be consistent with the curriculum to which children are being exposed. Tests that are to be commonly administered across countries need to keep in mind the variation in curricula across countries and to insure that the questions are equally appropriate for all the countries included in the study.

In designing the tests, it is important to keep in mind that there is a need for variation in the outcomes in order to distinguish better from worse academic attainment. While this may seem too obvious to mention, there are official curricula that are far more advanced than the material actually being covered in most schools. It is possible that even the best prepared students would not be able to answer questions based on the official curriculum. Therefore, questions have to be selected to reflect as broad a range of achievement as actually exists in the sample of children to be included in the sample.

DEMOGRAPHIC DIFFERENCES IN PERFORMANCE: It is common for average test performance to differ between demographic groups for reasons that are unrelated to child labor. For example, it is common for girls to outperform boys in language skills while boys outperform girls in mathematics. These differences are presumably unrelated to child labor, and yet boys and girls do differ in average incidence of child labor. These potential problems should be handled easily by the inclusion of dummy variable controls for different demographic groups, but the issue also points out the need for tests to cover more than one subject. If child labor has systematic effects on learning, then it should lower test scores in all areas.

V.IV.IV Instruments

Successful estimation of the impact of child labor on schooling outcomes must be able to control for the reverse causality of test scores on child labor. Children who are performing worse in school are more likely to enter the labor market at an early age. To derive unbiased estimates of the impact of child labor on test scores, we need to derive instruments for child labor: variables that vary the probability of child labor without also directly affecting test scores.

CHILD WAGES AND AGES: The discussion in section V.II indicates that measures of the opportunity cost of child time in school are good instruments for child labor. Child wage is self-explanatory, except that we would need the prevailing child wage by age for boys and girls in each school cluster. If wage is not available, the child age is a good substitute as wage and age should be closely related. However, child age is likely related to test scores, making it an invalid instrument. Older children in a given grade are likely to have been held back in the past. However, if the normal age of starting school varies across schools,[11] in different parts of the country, or if it varies across countries in multi-country samples, then one can differentiate child time in school from child's age using normal starting school age as a source of exogenous variation in the relationship between age and grade attained. Another alternative is if the age at which children can initially find work in the local labor market varies across school clusters. Note that if local child wage is available, it would be the preferable instrument.

LEGAL VARIATION: Differences in truancy laws, school starting ages, and preschool programs across countries can be used as instruments for child labor across countries. In addition, differences in ability to enforce laws, adhere to demographic principles, or other measures of government capacity of the sort discussed in Kaufmann et al. (2002) may vary the cost of compliance with child labor laws. The usefulness of these instruments is limited by the extent to which child labor varies across countries as opposed to within countries, as will be demonstrated in section V.VI.

RANDOMIZED TRIALS AND NATURAL EXPERIMENTS: If children are randomly assigned into child labor, one could use the difference in test scores across the two groups of children as the effect of child labor on school achievement. To our knowledge, that type of randomized trial has not been conducted and is unlikely to pass a human subjects review. However, several examples in Latin America closely approximate that type of experimental design. In Brazil, Honduras, Mexico, and Nicaragua, conditional transfer programs have been introduced which tie the receipt of income transfers from the government to proscribed household behaviors. In all the countries, receipt of the transfer was conditional on the child attending school. While receipt of the subsidy was not conditioned on the child not working, it appears that the incidence of child labor declined in Nicaragua (Maluccio, 2003) and in Mexico (Skoufias and Parker, 2003). In the Brazil Bolsa Escola program (Lavinas et al., 2003), child labor did not decline appreciably, but it declined sharply in the rural Brazil PETI program (Yap et al., 2003). What makes the experimental design in all these countries is that the programs were installed in village clusters so that some villages received the program in the first year of its existence and other observationally equivalent villages received the program in later years. The delayed implementation villages serve as controls for the early implementation villages. In Mexico, there was no appreciable change in test scores as a consequence of the reduction in child labor.[12]

Natural experiments would occur when some event changes child labor that is clearly unanticipated and outside the control of the households. One application is the impact of weather shocks on rural households. In India, rural households experience unanticipated temporary increases or decreases in farm income depending on the timing and quantity of the annual monsoon rains. Jacoby and Skoufias (1997) were able to show that adverse income shocks associated with poor rainfall caused households to increase child time in the labor market. The study did not have information on test scores so that we could determine if the increase in child labor was associated with changes in cognitive achievement. In the past, natural experiments tended to be country specific and accidental, so it is harder to think of a planned natural experiment that could be exploited to identify child labor, either in a single country or across countries.

V.V. Sampling Issues

Data sets geared toward studying child labor and school achievement need to address various concerns. One is the need to control for the endogeneity of child labor. If the data set is to be collected in a single country, this will require the collection of local child wages or other variables that may affect the probability of child labor at one point in time or over time. Cross-country data sets allow an added source of exogenous variation in child labor, that being a different legal climate concerning the regulation of child time at work and in school.

After deciding if the data set will cover one or more countries, a second decision is whether the sample should be a random draw of the population as a whole or to concentrate on a few communities. Random samples are more expensive to collect, particularly if the survey is administered in face-to-face interviews rather than self-administered questionnaires. The latter may be impossible in countries where many adults are illiterate and thus unable to answer questions without assistance. Moreover, if the data set involves the administration of achievement tests, it is more convenient to test the children in groups than one at a time at home. While it is technically possible to have a random sample with administered achievement tests, in practice such data sets are collected in clusters. As a matter of convenience, a properly administered random sample requires good knowledge of the population universe. Many countries lack sufficiently reliable census information from which to base a random sample, so basing the sample on lists of schools or communities may be the only available option.

The clusters could be centered around schools or around villages. The advantage of basing the clusters on schools is that it is easy to identify large numbers of children of like age or grade. The problem is that when all children are selected from school records, only children in schools are sampled. By design, these school-based samples will miss children of like age who are not enrolled in school. This selection problem will be most severe in countries with low enrollment rates. An alternative is to base the clusters on villages and then to interview households that have children in the required age range, whether or not the children are in school. This would allow the educational production function estimation to control for the selection of children into school. Alternatively, a school-based sample could be supplemented by the inclusion of children not in school from the same community. It would be necessary to know the proportions of children in and out of school to apply proper weights to the two groups.

The adverse impacts of child labor may take time to develop. Any given cross section that elicits information on current child labor may miss past child labor. Two children who are both working differently may have very different past experiences with child labor. In addition, evidence suggests that many spells of child labor may be short lived, so the proportion of children who work at least part of a year is larger than the proportion of children who work at any one point in the year. Even in a cross sectional data set, retrospective questions on whether the child has ever worked in prior years or in the current year may yield more accurate information than questions concentrating on current work status.

Examples of various data sets that have been used to analyze various aspects of child labor and schooling investment are presented below.

V.V.I Latin-American Laboratory of Quality of Education (LLECE)

In 1997, the First Comparative International Study on Language, Mathematics and Associated Factors was administered in 12 countries of Latin America. This data set is discussed in great detail in Chapter III. To our knowledge, this is the best existing data set combining information on child labor and school outcomes for younger children in developing countries however no information on children not in school was collected.

V.V.II The Third International Mathematics and Science Study (TIMSS)

The International Study Center at Boston College oversaw the collection of the TIMSS in 1995. A follow-up sample is being prepared. The TIMSS is the largest international study of student achievement ever conducted. A more detailed description of the data set is provided in Chapter IV. Our analysis concentrates on the 7th and 8th grade samples from the poorer countries in the sample.[13] The focus on the lower income countries was dictated by our interest in child labor, which is less common at these ages in OECD countries which make up the majority of the 40 countries included in the TIMSS. The countries we use included Colombia, Czech Republic, Hungary, Iran, Latvia, Lithuania, Romania, Russia, Slovak Republic and Thailand.[14] While all of these countries fall in the lower-middle-income class or the lower part of the upper middle-income class classification from the 1998 World Development Report, none are as poor as the lower tail of the Latin American sample.

As with the Latin America data, the TIMSS was a stratified sample drawn from lists of schools of different sizes. In each school, a 7th and 8th grade class was selected for the study, and all students in the classroom were tested and interviewed. In the TIMSS, some countries applied a third stage by sampling students within classrooms. Information was also collected from teachers, students and principals through questionnaires. No information was collected from parents.

V.V.III International Crops Research Institute for the Semi-Arid Tropics (ICRISAT)

The ICRISAT sample is a heavily researched household survey conducted on 40 households in ten rural villages in India. The questionnaire was administered in person by a trained survey team. The data set includes information on time allocation of children as well as adults, but it does not include information on schooling outcomes. It has the additional feature that it includes repeated observations on households over time, so that individual specific unobservable fixed effects can be controlled, unlike the case with single cross sections. The longest period of observation is from 1975 through 1984 for three villages, while others were observed for shorter time periods. The data set has proven useful for studying the determinants of child labor and school enrollment, but it cannot address the impact of child labor on school achievement.

Another advantage of the ICRISAT data set is that it is a community-based and not a school-based sample. This means that one can observe children both in school and out of school, side-stepping the selection problem inherent in samples that include only children enrolled in school.

V.V.IV Living Standards Measurement Surveys (LSMS)

The ICRISAT data set was a precursor of the detailed household surveys designed and implemented by the World Bank in a broad range of countries. The first LSMS was collected in 1985 in the Cote d'Ivoire and Peru. They are characterized by very detailed modules covering labor supply behavior of all household members over age six plus information on consumption, health, production, fertility, schooling, and wealth indicators. The household information is supplemented by community information including the location and quality of educational, health, water, transportation and other public services.

The survey also collects information on commodity prices. Such data allow very detailed studies of factors affecting child labor and time in school, but have not included measures of school achievement. The questionnaire was administered in the household by trained interviewers.

The LSMS has the advantage that parallel modules are administered in many different countries, allowing cross country comparisons to be drawn. This allows cross-country variation in truancy of child labor laws to serve as potential instruments for child labor. The data are of extremely high quality without missing responses because of the use of face-to-face interviews rather than self-administered questionnaires. This avoids problems related to selection on the basis of the literacy of the respondent. Information on all household members is collected, so potential substitution of one child's time for another can be analyzed. The LSMS data sets are very good sources of information for the study of the determinants of child labor and its impact on school enrollment. However, the absence of test scores means that the analysis cannot be carried forward to studies of school achievement.

V.V.V The Pesquisa Nacional por Amostra de Domicilios (PNAD)

The PNAD is an annual household survey conducted by the government of Brazil. The survey, which covers roughly 100,000 households, is designed to monitor the socioeconomic characteristics of the population, including education, labor supply, residency and earnings. The survey adds additional questions which change year-to-year to allow other empirical investigations on topics such as health or fertility. Several recent waves of the PNAD included retrospective questions on when the respondent first entered the labor market. Therefore, even though each wave is an independent cross-section of the Brazilian population, one can address questions that have life cycle dimensions. Recent studies have addressed how child labor affects earnings, poverty status, and returns to schooling as an adult. The PNAD has also been used to examine whether child labor is more common in households where the parents also worked as children.

The PNAD does not allow the incorporation of school quality measures or other local public service attributes. It also does not include information on test scores. However, it is the only data set of which we are aware that includes retrospective data to accommodate the longitudinal aspects of child labor.

V.V.VI The Statistical Information and Monitoring Programme on Child Labour

The Statistical Information and Monitoring Programme on Child Labour, SIMPOC, is the statistics and monitoring unit of the International Programme on the Elimination of Child Labour (IPEC), a part of the International Labour Organization (ILO).

SIMPOC has undertaken several different types of surveys. Two survey types can be used to evaluate the consequences of child work on schooling outcomes. The National Surveys are household surveys used to generate countrywide data on the economic activities of children from 5 to 17 years of age. Several National Surveys are currently being conducted, the most recent completed one being a 2002 survey of 12,000 households and 69,549 individuals in Cambodia. The National Surveys collect information about child labor type and frequency, household, and socio-economic attributes, enrollment and attendance rates and in some cases, measures of dropout, grade-for-age, falling behind in school and years of schooling attained. The National Surveys do not collect any information on teacher attributes or test scores.

The School-based Surveys collect information on working children who also attend school. The School-based Surveys get teachers' and administrators' perceptions of the intensity of child labor in the local labor market and on how child laborers perform in school.

Qualitative responses include perceived absenteeism rates, promotion rates and other schooling outcomes for students who work relative to those who do not work. The survey also elicits impressions of the school-related factors that may influence the incidence of child work, such as the quality of the school and the children's perception of the relevance of their education.

V.VI. Sample Results from the TIMSS Sample

In this section, we demonstrate the type of results that can be obtained with the TIMSS multi-country data set that include both measures of child labor and test scores. One of the potential benefits of multi-country data sets is that differences in legal environment can serve as exogenous variables shifting the probability of child labor. Unfortunately, the analysis of variance suggests that the use of country-specific effects may be a weak source of identification. The reason is that less than five percent of the variation in child labor is attributable to factors that vary across countries. The rest is due to within country variation. This suggests that a successful study must be able to utilize instruments that vary within country as well as across countries.

Estimation of the impact of child labor on test scores involves two equations, the labor supply equation (IV.2) and the educational production function equation (IV.3). The variables used in the labor supply equation are reported as exogenous variables and instruments in Tables IV.1b and IV.2c. Variables used in the educational production are the exogenous variables excluding the instruments.

V.VI.1 Child Labor Supply Estimates

Table V.1 shows the frequency of paid child labor in the various countries in the TIMSS data. Overall child labor rates are the highest in Columbia, Romania and Thailand while the lowest incidences of child work are found in Russia and Slovak Republic. In Romania and Thailand most children that work in the paid labor market work only a few hours per day, while in Columbia almost half of the children that work work five hours per day or more.

Although the labor supply estimates are interesting in their own right, they are not our primary concern in this chapter. In general, the estimates are consistent with expectations of how school quality, opportunity costs, and parental socioeconomic status would influence child time allocations. Being a boy and living in a rural area increases the likelihood of working in the child labor market. Working outside the home increases with age because both physical and mental ability to do work increase with age. The likelihood of working decreases the higher the education of the father. Speaking the language of the test at home, small family size, living with both parents and having a large number of books at home lowers the incidence of working in the labor market. Generally, school attributes associated with improved school quality lower the incidence of child labor. The country-level measures also proved significant in explaining variation in child labor across countries. The detailed results for the estimate of child labor at a paid job are reported in Table IV.3 (Chapter IV). A detailed variable description can be found in Table IV.1b and summary statistics in Table IV.2c. For working inside the home we encountered identification problems. It seemed that working in the home could not be properly identified with the instruments we had at hand and we therefore suspect that working in the household is truly exogenous or, more likely, that we do not have the proper instruments.

V.VI.II Child Labor and School Achievement

Child labor can be treated as endogenous or exogenous. If it is truly jointly determined with cognitive achievement as expected, then the coefficients from equations treating child labor as exogenous will be biased. We demonstrate this point using alternative measures of child labor.

Table V.2 contains variable definitions and sample statistics for alternative measures of cognitive achievement and child labor. In the TIMSS data set, child labor is measured alternatively by an ordered variable indicating the range of hours of work outside the home, and again by a series of dummy variables indicating the relevant hour range. Cognitive achievement is measured by tests of mathematics and science administered to children in the 7th and 8th grades. When treated as endogenous, first stage regressions were estimated using ordered probit and the predicted values are used in the second stage educational production function. Standard errors are estimated using a bootstrapping procedure.

The two first columns in Table V.3 show the results of working at a paid job on test scores from modeling child work exogenously. The results use a dummy variable to indicate the range of hours worked per day. Using zero hours of work as the reference, we estimate the impact of being in work groups of less than one hour per day, 1-2 hours, and 3-5 hours. For work in the home, the reference group is less than one hour per day versus 1-2 hours per day.[15] The results from the exogenous models suggest that the more a child works at a paid job per day the more serious the impact on test scores. Compared to children not working in the labor market at all, test scores, both mathematics and science, are lowered even if the child only works less than one hour a day at a paid job, and even lower for children working 1-2 and 3-5 hours daily. The implied proportional change in test scores relative to the mean is reported under the coefficient and its standard error. The estimates reflect the change in test scores from a movement from no work to the respective work-hours category, evaluated at sample means. The proportional change in test scores are small. Working at a paid job only lowered average test scores by between one to three percent.

Controlling for endogeneity, column three and four in Table V.3, jobs involving under an hour a day outside the home lower science but not mathematics scores and the proportional effects are very small. However, working more than an hour per day outside the home has a much larger adverse impact, lowering scores by between 11 percent and 14 percent.

Other exogenous variables behave as presumed. Boys do better than girls on both tests, and older students do better than younger students. The significant coefficient on age can most likely be explained by the fact that eighth graders perform better than seventh graders on the same test. Having educated parents increase test scores as do living with both parents, having a small family and having many books in the home. Speaking the language of the test frequently at home actually lowers mathematics scores but is insignificant in the science equation.

Among the teacher attributes, older, well-educated teachers produce better students than young teachers without significant education. Similarly, female teachers outperform male teachers. School and community attributes produce mixed results between the mathematics and language equations and do not always produce significant effects.

In Table V.4 working in the labor market and working in the household have been combined and are both included as exogenous regressors for test scores. Combining the two types of work does not change the effect of working on the schooling outcome. In the exogenous models, working many hours per day in the labor market lowers test scores, the more hours worked, the lower the test score. The proportional decrease in scores is never more than three percent. Working in the household one to two hours per day increases attainment compared to working less than one hour at home when work is taken as exogenous. The corresponding proportional increases in test scores are less than one percent on both tests.

Comparing the exogenous models with the endogenous models the increase in magnitude of the effect of working one to two hours and three to five hours are striking. Modeling work in the child labor market endogenously yields much larger negative impacts on school performance due to the fact that we now allow test scores to work both as a consequence and a cause of child labor. Except for working less than one hour per day at a paid job in the mathematics equation, the more the child works outside the home, the more severe the reduction in test scores. For children working more than one hour at a paid job, average scores went down by between ten and 16 percent. Also, working one to two hours in the home lowers test scores compared to children who work less than one hour per day in the home.

The conclusions from our preliminary investigation of these two data sets are that 1) child labor has adverse consequences for test scores; 2) the effects are not dramatically large but are statistically significant; 3) the adverse effects get larger as work hours increase; 4) it matters if child labor is treated as endogenous rather than exogenous; and 5) treating child labor as exogenous biases the estimated effect of child labor on test scores upward, so that the adverse impact of child labor on test scores gets smaller and may even reverse sign.

V.VII. Previous Empirical Studies

V.VII.1 Child Labor and Time in School

In addition to the review of the literature in Chapters III and IV a few other studies on child labor and time in school need to be addressed. It has been commonly observed that in many countries, the majority of working children are enrolled in school. For example, Ravallion and Wodon (2000) found that increases in enrollment in a sample of girls in Bangladesh were not associated with appreciable decreases in child labor. They conclude that the adverse consequences of child labor on human capital development are likely to be small.

However, it is possible that working children remain enrolled in school but do not attend as regularly. Several recent studies have examined that possibility. Boozer and Suri (2001) studied children aged 7-18 in Ghana in the late 1980s. They conclude that an hour of child labor reduced school attendance by approximately 0.38 hours. Another study by Edmonds and Pavcnik (2002), using a panel of Vietnamese households, found that increases in the real price of rice, a major export, lowered child labor. The reductions in child work were largest for girls of secondary school age who also experienced the largest increase in school attendance. Edmonds (2002) examined how child labor and education in a sample of poor black households in South Africa responded to a fully anticipated increase in government transfer income. Households that were eligible for a social pension program experienced a sizeable decrease in child labor and an increase in schooling attendance.

While child labor appears to be associated with reductions in school attendance, it still does not follow that child labor lowers the development of marketable skills. Many schools in developing countries are of poor quality so that children may receive better informal or on-the-job training outside school. On the other hand, changes in attendance may understate the adverse effect of child labor on human capital accumulation if children who attend school while working may learn less in school if working takes away valuable study time during the day and makes the child too tired to learn.

Emerson and Souza (2002) explore the impact of one child's working on their siblings. Because earlier-born children are able to command higher wages than their younger brothers and sisters, this additional income may allow parents to send the late-born siblings to school. They found that in Brazil first-born males were more likely to work than their younger siblings and male last-born children are less likely to work as child laborers than their earlier-born siblings. For girls, first-borns are less likely to go to school than later born girls. This possibility that child labor adds schooling opportunity through income reallocations within the household has not been adequately explored.

V.VII.II Child Labor and School Achievement

Similarly as for child labor and school attendance the review of previous studies on child labor and achievement from Chapters III and IV can be further extended. There is indirect evidence that child labor limits a child's human capital development. A definitive answer on whether child labor lowers cognitive attainment requires direct estimation of the educational production function (IV.3).

The National Research Council and Institute of Medicine (1998), found no effects of working part-time on time spent on homework for U.S. tenth graders, in part because time spent on homework by U.S students is already relatively modest. Consequently, neither type of work nor hours of work per week are likely to influence the amount of time spent on homework. Work was not completely innocuous, however. Students who worked while in school experienced higher rates of behavioral problems such as alcohol and drug use and minor delinquency. Furthermore, the study found that students who worked in tenth grade selected undemanding classes to maintain their GPA.

Some studies have found stronger evidence of adverse consequences of child labor on achievement. Stern (1997) found that working more than 15 hours per week while in secondary school led to lower grades, less time spent on homework, increased likelihood of dropout and a lower likelihood of entering post-secondary education. Similar findings are reported by Cheng (1995) and StatsCan (Canadian Social Trends, 1994). Singh and Ozturk (2000) explored the linkage between working hours and achievement in the U.S. and reported that an increase in hours of part-time work lowered the number of mathematics and science classes taken which in turn led to lower achievement in mathematics and science. Barone (1993) found that younger students working long hours performed more poorly than did working older students.

As discussed both in Chapter III and Chapter IV, the impact of working on learning while in high school or college in developed countries may be very much different than that of young children working in developing countries. School attainment is presumed to decrease as child labor increases because working while in school disturbs the learning of basic numeracy and literacy. The more the child works, the lower the school attainment. However, the number of studies tying child labor to test scores in developing countries is very small.

V.VIII. Gaps in the Research Record

As the review of the literature suggests, there are very few studies of the impact of child labor on cognitive achievement at the primary level. Most studies are still in working paper form, so it is probable that there are other studies of which we are not yet aware.

Nevertheless, these are the gaps in our knowledge of the damage caused by child labor based on the literature that we have been able to identify.

To our knowledge, no studies of the effect of child labor on student achievement have made use of the "value added" approach that allows for control of unmeasured child ability. Because child ability is likely to be correlated with child labor also, standard instrumental variable techniques may still yield biased estimates.

Moreover, very few studies have controlled for endogenous child labor. Those that have, had to make use of arbitrary identification restrictions or relatively limited cross-country variation in the legal environment concerning child labor. A more definitive study will require the collection of better exogenous shocks to the child labor supply equation, beginning with local wages offered for child workers.

Another useful extension would be to integrate standardized tests into the conditional transfer programs tied to reductions in child labor. Although such programs have been recently introduced in several Latin America countries, most are not tied directly to child labor with the exception of the PETI in Brazil. The advantage of explicit randomization in the implementation of these programs is that the reliance on potentially weak identification restrictions for child labor can be avoided.

Evidence suggests that a significant proportion of child labor spells are short-lived. Some are in response to unanticipated transitory shocks to household income. We do not know if short-term spells of child labor have permanent adverse effects on learning, nor do we know if the spells that are due to unforeseen transitory income shocks are more damaging than those which were planned.

Only two studies have been able to examine work in the home versus work in the market. Evidence appears to suggest that work in the home is less damaging to school achievement than is market work, but more work is needed. Similarly, we do not know if the damage differs by the type of work children do, or if it is subject to the hours worked alone. We do not know if there is a threshold level of hours of work at which damage begins, or if any child labor causes damage. We have only a few studies that have examined the long-term economic consequences of child labor, and work on long-term health consequences of child labor is even more limited.

V.IX. Type of Complementary Data That Could Supplement Household Data Sets

The type of data required to test the impact of child labor on school achievement is laid out in section V.IV. The critical need for auxiliary data is to collect information that will help identify work inside or outside the home. These are a few suggestions.
1) Collect two test scores, one at the beginning of the school year and one at the end. This will allow estimation of the value added specification. 2) Information on the labor market for children can be obtained by aggregating responses on wages paid to children from household surveys in the same community. Alternatively, one can acquire information on employment opportunities and child wages by interviewing informed members of the community. 3) Any information that could vary the cost or return to child labor or schooling across communities would be useful. School quality indicators are the most obvious, but they would be related to both child labor and cognitive achievement. What is needed are factors that vary across communities that affect child labor but are not related to test scores. 4) It is important to know the legal climate surrounding child labor and schooling in the country. At what age does a child enter school, what is the truancy age, how long is the school day, and how long

is the school year? It is conceivable that some of this information would vary across communities within a country. However, this information is more useful in data sets that span countries, as changes in the legal environment can serve as an instrument for differences in the probability of child labor across countries.

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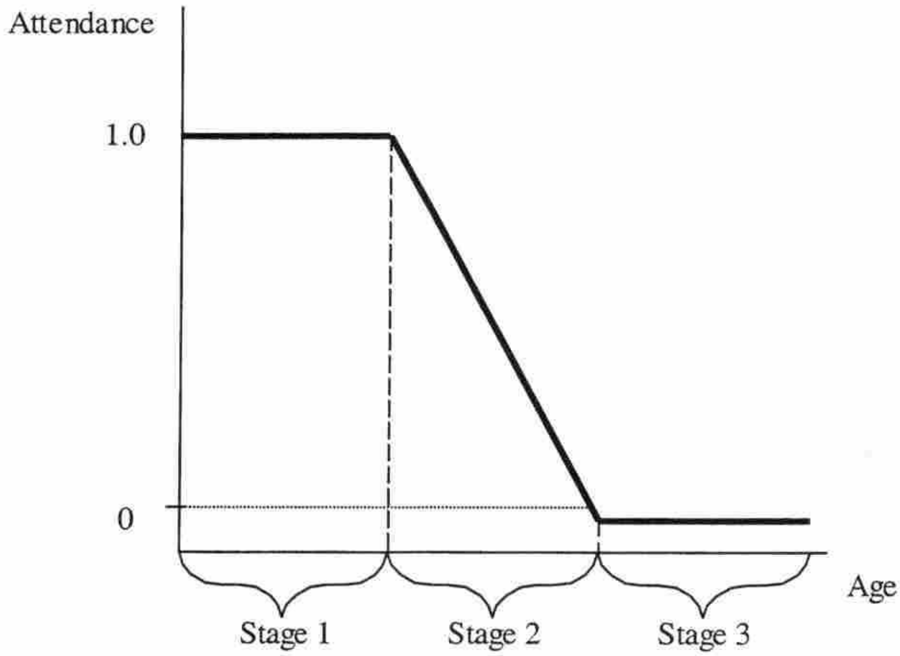

Figure V.1 Stages of Investment in School.

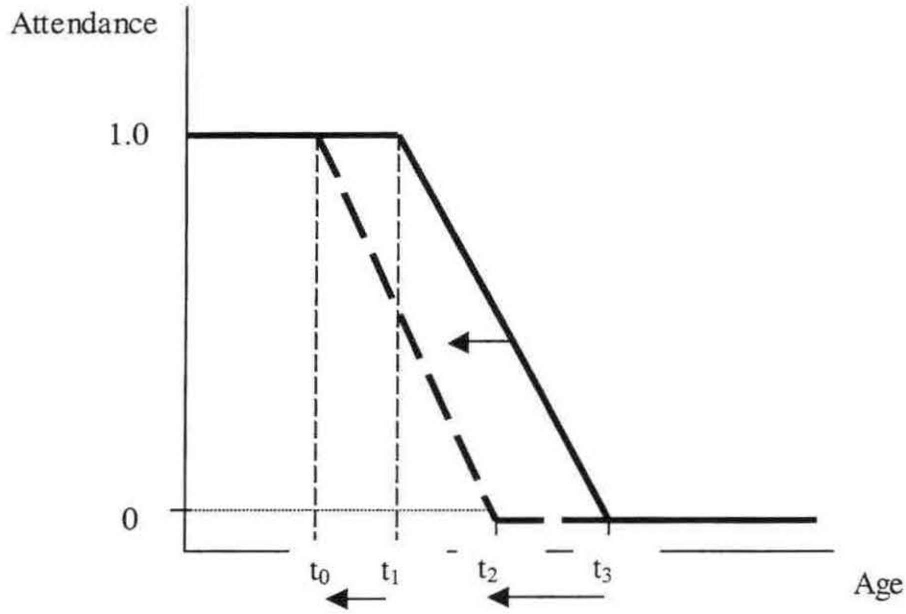

Figure V.2 Impact of Adverse Income Shocks or Child Wage Increases on Investment in School.

Table V.1 Country Level Child Labor at a Paid Job in the TIMSS data.

Country	N	Child Labor[a] (%)	< 1 hr.[b] (%)	1-2 hrs.[b] (%)	3-5 hrs.[b] (%)	> 5 hrs.[b] (%)
Colombia	4102	0.294	0.059	0.048	0.051	0.136
Czech Republic	6437	0.225	0.073	0.068	0.035	0.049
Hungary	5570	0.183	0.058	0.057	0.033	0.036
Iran	5399	0.256	0.052	0.061	0.064	0.079
Latvia	4156	0.195	0.053	0.062	0.038	0.042
Lithuania	4001	0.248	0.061	0.077	0.046	0.063
Romania	6799	0.289	0.172	0.043	0.030	0.044
Russia	6755	0.096	0.029	0.032	0.019	0.015
Slovak Republic	6855	0.141	0.048	0.048	0.026	0.018
Thailand	10910	0.390	0.124	0.123	0.052	0.091
All Countries	60984	0.232	0.073	0.062	0.039	0.057

[a] Child indicates whether s/he works at least sometime per day in the paid labor market when not in school.
[b] Percent child laborers working < 1 hr., 1-2 hrs., 3-5 hrs. or >5 hrs. per day out of the total number of observations in that country.

Table V.2 Variable Description and Summary Statistics TIMSS Data.

< 1hr. Paid	Dummy if student works less than 1hr. per day at a paid job (C)
1-2 hrs. Paid	Dummy if student works 1-2 hrs. per day at a paid job (C)
3-5 hrs. Paid	Dummy if student works 3-5 hrs. per day at a paid job (C)
1-2 hrs. Home	Dummy if student works 1-2 hrs. per day in the household (C)

Variable	N	Mean	Std. Dev.	Min	Max
Math Score	69790	480.390	95.348	180.870	795.413
Science Score	69790	487.378	94.929	82.440	806.714
Work Paid	60984	1.555	1.137	1	5
Work at Home	65885	2.745	0.894	1	5
< 1hr. Paid	60984	0.079	0.270	0	1
1-2 hrs. Paid	60984	0.066	0.249	0	1
3-5 hrs. Paid	60984	0.039	0.194	0	1
1-2 hrs. Home	65885	0.422	0.494	0	1

Sources: C: Child survey.

Table V.3 Least Squares and Instrumental Variables Equations on Test Scores using Work at a Paid Job as a Measure of Child Labor.

	Child Labor Exogenous[a]		Child Labor Endogenous[b]	
Variable	**Mathematics**	**Science**	**Mathematics**	**Science**
Work at Paid Job				
< 1 hr. Paid	-3.884*	-7.388*	0.559	-9.267*
	(1.331)	(1.360)	(2.899)	(2.978)
Proportion[c]	-0.008	-0.015	0.001	-0.019
1-2 hrs. Paid	-9.101*	-7.537*	-50.737*	-66.377*
	(1.448)	(1.480)	(5.963)	(8.001)
Proportion	-0.019	-0.015	-0.106	-0.136
3-5 hrs. Paid	-14.421*	-11.332*	-60.402*	-62.499*
	(1.875)	(1.916)	(9.937)	(11.291)
Proportion	-0.030	-0.023	-0.126	-0.128
Child				
Age	5.719*	9.352*	6.334*	10.412*
	(0.427)	(0.437)	(0.457)	(0.426)
Boy	6.625*	18.274*	6.315*	18.167*
	(0.737)	(0.754)	(0.812)	(0.707)
Parents/Household				
Mother's Educ	3.124*	1.428*	3.213*	1.545*
	(0.331)	(0.338)	(0.339)	(0.331)
Father's Educ	3.382*	3.024*	3.477*	3.128*
	(0.329)	(0.336)	(0.360)	(0.334)
Test Language	-0.589	-3.047*	-0.358	-3.255*
	(0.835)	(0.854)	(0.712)	(0.804)
People Home	-6.046*	-5.317*	-5.962*	-5.083*
	(0.223)	(0.228)	(0.211)	(0.251)
Both Parents	9.037*	9.294*	8.982*	9.038*
	(0.743)	(0.759)	(0.741)	(0.850)
Books at Home	16.429*	14.455*	16.446*	14.484*
	(0.322)	(0.329)	(0.312)	(0.321)
Teacher				
Teacher Age	3.173*	2.409*	3.165*	2.348*
	(0.380)	(0.389)	(0.402)	(0.463)
Male	-11.313*	-8.644*	-11.074*	-8.375*
	(0.924)	(0.944)	(1.071)	(0.931)
Teacher Educ	10.611*	9.274*	10.576*	9.292*
	(0.268)	(0.273)	(0.287)	(0.298)
School				
Total Enr	0.009*	-0.003*	0.009*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Girls Enr	0.056*	0.036	0.056*	0.031
	(0.025)	(0.026)	(0.022)	(0.022)
Shortage	0.013	-0.898*	-0.009	-0.910*
	(0.140)	(0.143)	(0.144)	(0.136)
Class Size	0.429*	1.030	0.411*	1.018

Table V.3 (Continued)

Variable	Child Labor Exogenous[a] Mathematics	Science	Child Labor Endogenous[b] Mathematics	Science
	(0.052)	(0.054)	(0.058)	(0.057)
Community				
Rural	3.188*	-0.515	2.676*	-0.856
	(0.847)	(0.865)	(0.893)	(0.804)
Constant	261.120*	227.354*	251.717*	210.427*
	(7.399)	(7.562)	(7.415)	(8.114)
R^2	0.223	0.182	0.223	0.183
N	56247	56247	56247	56247

[a] Standard errors in parentheses. [b] Bootstrap standard errors in parentheses. * indicates significance at the 0.05 confidence level. [c] Proportional change in test scores associated with moving from the reference group to the dummy variable group. Regressions also include dummy variables controlling for missing values.

Table V.4 Least Squares and Instrumental Variables Equations on Test Scores using Work at a Paid Job and Work at Home as Measures of Child Labor.

	Child Labor Exogenous[a]		Child Labor Endogenous[b]	
Variable	**Mathematics**	**Science**	**Mathematics**	**Science**
Work at Paid Job				
< 1 hr. Paid	-3.756*	-7.350*	6.409*	-5.641*
	(1.344)	(1.373)	(3.118)	(3.010)
Proportion[c]	-0.008	-0.015	0.013	-0.012
1-2 hrs. Paid	-9.013*	-7.789*	-56.434*	-71.249*
	(1.465)	(1.497)	(6.799)	(7.563)
Proportion	-0.019	-0.016	-0.117	-0.146
3-5 hrs. Paid	-14.579*	-11.624*	-48.767*	-55.934*
	(1.905)	(1.946)	(11.618)	(13.792)
Proportion	-0.030	-0.024	-0.102	-0.115
Work at Home				
1-2 hrs. Home	2.476*	4.402*	-8.355*	-4.039*
	(0.728)	(0.743)	(1.349)	(1.348)
Proportion[c]	0.005	0.009	-0.017	-0.008
Child				
Age	6.035*	9.747*	6.522*	10.626*
	(0.433)	(0.442)	(0.507)	(0.515)
Boy	7.291*	19.135*	2.522*	16.431*
	(0.750)	(0.766)	(0.912)	(1.029)
Parents/Household				
Mother's Educ	3.078*	1.386*	3.066*	1.438*
	(0.334)	(0.341)	(0.366)	(0.352)
Father's Educ	3.441*	3.081*	3.408*	3.105*
	(0.332)	(0.339)	(0.353)	(0.323)
Test Language	-0.563	-3.080*	-0.089	-2.897*
	(0.847)	(0.865)	(0.782)	(0.799)
People Home	-6.030*	-5.301*	-5.800*	-5.032*
	(0.226)	(0.231)	(0.217)	(0.256)
Both Parents	8.820*	9.045*	9.117*	9.087*
	(0.750)	(0.767)	(0.733)	(0.793)
Books at Home	16.447*	14.415*	16.507*	14.510*
	(0.325)	(0.332)	(0.325)	(0.331)
Teacher				
Teacher Age	3.233*	2.455*	3.068*	2.290*
	(0.384)	(0.393)	(0.409)	(0.364)
Male	-11.055*	-8.434*	-10.463*	-8.044*
	(0.933)	(0.953)	(0.927)	(0.931)
Teacher Educ	10.622*	9.257*	10.240*	9.123*
	(0.271)	(0.276)	(0.250)	(0.288)
School				
Total Enr	0.009*	-0.003*	0.009*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Girls Enr	0.076*	0.055*	0.039	0.028

Table V.4 (Continued)

Variable	Child Labor Exogenous[a] Mathematics	Science	Child Labor Endogenous[b] Mathematics	Science
	(0.025)	(0.026)	(0.022)	(0.023)
Shortage	0.031	-0.914*	-0.013	-0.923*
	(0.142)	(0.145)	(0.144)	(0.135)
Class Size	0.402*	0.993*	0.402*	0.996
	(0.053)	(0.054)	(0.054)	(0.049)
Community				
Rural	2.913*	-0.805	4.760*	0.197
	(0.856)	(0.874)	(0.812)	(0.900)
Constant	255.427*	220.703*	260.292*	213.665*
	(7.498)	(7.660)	(8.278)	(8.872)
R^2	0.222	0.181	0.221	0.181
N	55139	55139	55139	55139

[a] Standard errors in parentheses. [b] Bootstrap standard errors in parentheses. * indicates significance at the 0.05 confidence level. [c] Proportional change in test scores associated with moving from the reference group to the dummy variable group. Regressions also include dummy variables controlling for missing values.

Endnotes

[1] Numerous studies have shown that child labor and time in school are sensitive to changes in pecuniary costs and returns. Nonpecuniary costs and returns are also likely to be important, but are difficult to quantify. Most studies control for them using measures of household demographics and other proxies for local tastes toward schooling and child work.

[2] This allows for some increasing returns to schooling in the first few years of school. There is considerable evidence supporting the assumption of diminishing returns to schooling. Psacharopoulos (1994) presents the results of 57 studies of returns to schooling and average years of schooling in developing countries. A regression of estimated returns on years of schooling suggests that for each additional year of schooling, returns fall by 0.8 percentage points. Lam and Schoeni (1993) conducted a detailed examination of how rates of return to schooling changed as schooling increased in Brazil. After controlling for detailed family background variables, they found that the highest returns were to the first four years of schooling with nearly linear returns thereafter. Card's (1999) review of the recent literature also concludes, albeit tentatively, that returns fall with years of education. It should be noted that finite life spans and rising opportunity costs of time as an individual ages guarantee that the returns to schooling must fall eventually.

[3] One referee of the paper pointed out that not all data sets find monotonic reductions in child schooling, but that possibility can be accommodated by cyclical income shocks in the face of liquidity constraints in the current model. In the case of certain future income streams and perfect credit markets, time in school will fall as the child ages as in Ben Porath's original formulation. We should note that in virtually all countries, the general pattern of declining enrollment rates and rising labor force participation with age is observed.

[4] Returns can also be characterized in terms of increased utility rather than increased earnings.

[5] This would be the case if local wages for children were set strictly on the child's age and physical stature and not on the child's school attainment. In fact, most jobs for children do not require literacy or numeracy, so it is likely that at least at the lowest grade levels, the child's current wage does not reflect past school attainment. Credit constraints or very high discount rates will also create a situation where current and future wages can vary independently.

[6] Labor income will reflect endogenous choices on child and adult labor supply. Nonlabor income will reflect returns on assets, remittances from abroad, government transfer payments and other income unrelated to labor supply.

[7] This would be true if household income and school inputs are complements. This would happen if higher income parents invest more in tutoring, supplementary educational materials, or other inputs that may reinforce what children learn in school. Alternatively, wealthier parents may put pressure on the school to make efficient use of its resources.

[8] Note that many forms child labor do not fit under this categorization, and yet will still be harmful if they limit time or productivity in school or leave the child tired and more susceptible to illness.

[9] An exception is King et al. (1999) who integrated school attendance records into their household survey. This is easier to do in samples that include many children from a single school.

[10] King et al. (1999) examined whether social promotion increased the probability that a child continued in school in the Northwest Frontier Province of Pakistan. They found that promotions based on attendance and performance on tests increased the probability of continuation, but that promotions that were unrelated to school performance had virtually no effect on continuation. Consequently, continuation may be a better indicator of school performance than is promotion.

[11] Some country school systems may have different school starting ages in different parts of the country. Alternatively, multi-country samples will often include country systems with different school starting ages.

[12] It should be noted that there are many changes occurring at the same time (improvements in public services, implementation of health and nutrition programs, training programs, etc.). Therefore it is difficult to associate changes solely to the implied change in child labor.

[13] Even though the TIMSS collected data for 3rd and 4th graders as well, the data on these grades were not collected for many of the developing countries and did not prove useful for our work on child labor and school achievement.

[14] The useable TIMSS sample is much smaller than one would guess from the Web Page. Several developing countries (Bulgaria, Kuwait, Philippines, South Africa) excluded important variables to this topic and many observations from the included countries had missing values.

[15] In the TIMSS data set, no children were predicted to work zero hours per day in the home or more than two hours per day in the home, so we shrank the number of options to reflect that outcome.

Chapter VI. General Conclusions

VI.I. General Results

Summing up the individual conclusions from each of the chapters I conclude that the results from this study support the results from previous research. The preponderance of evidence suggests that child labor is strongly tied to the level of household incomes. In fact, increases in per capita incomes can explain almost all of the reductions in child labor worldwide since 1950. However, child labor becomes less responsive to additional increases in per capita income as the level of per capita income rises. Working while in school, even very few hours per day, reduces learning and therefore also cognitive ability. Even occasional child workers face a substantial loss of school achievement as a result of their work. In addition, the estimates of the lost cognitive ability associated with child labor are consistent with estimates of the wage loss adults suffer from having worked as a child.

Further to other findings however, the results emphasize that the outcomes hold across a large number of countries and cultures as well as for children of varying ages and in varying stages in school. Moreover, the results point at the endogenous relationship between child labor and schooling and suggest that households make joint decisions in allocating children's time to working, schooling and learning. When treating child labor as endogenous the adverse effects of learning are greatly magnified suggesting that the previously believed size of the effects of combining schooling with work have been underestimated.

VI.II. Implications

The policy implications from the finding are profound. There is a cost of combining children's schooling with work. The lost cognitive ability and implied adult earnings loss from working as a child are large enough to suggest that the expenses of combating child labor can be recovered in part from higher earnings of the children when they enter adulthood.

Moreover, future studies on child labor and schooling should primarily focus on the effect of working on achievement, preferably in terms of test scores. Improvements in sampling methods and estimation techniques could be made by controlling for unobserved ability bias. The "value added" approach discussed in Chapter V could be used to remove some of this bias from predicted learning achievement. However, this method requires subsequent testing of children in order to factor out the learning over a period of time. Also, because we do not know much about local labor market conditions, and, because they to a great extent determine the demand for children's work, future studies should extract as much information about local markets as possible. The wage that children can earn, for instance, is a very important determinant of how much children will work.

Another important implication of the findings is that programs that target the supply of child labor could be successful. Subsidizing household income, improving school productivity and lengthening the school day decreases the opportunity cost of working and the investment that parents make sending their children to school are more likely to pay off. Bolsa Escola, PROGRESA, PETI (discussed in Chapter V) and several others are examples of targeted income transfer programs that all have succeeded in lowering the incidence of child labor. No testing was undertaken when evaluating these programs but would have been of great interest in order to assess the effect of the programs on learning achievement.