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Mario A. Sanchez
Peter F. Orazem
Victoria Gunnarsson

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*Excerpts obtained from the IADB/WB joint book on child labor in LAC

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The previous chapters have 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 (Chapter 5) also found that child labor lowers the rate of return per year of education, suggesting 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.

Surprisingly few studies have examined how child labor affects schooling outcomes. Those that do 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 drop-out. 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 grade point averages 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

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longer hours harms academic achievement. Howard (1998) found that A-level grades in England declined when students worked more than 15 hours per week, and Singh (1998) reported a modest decrease in U.S. achievement test scores as hours worked increased.

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 be more complementary with schooling than the low-skilled, manual work performed by young children in developing countries. Older children also may be more able to absorb the physical demands of combining school and work, whereas younger children may find that labor leaves them too tired to keep up with school.

No studies have been found on 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 children 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.

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the use of the data. Donna Otto prepared the manuscript. Views expressed are not necessarily those of the World Bank or the Inter-American Development Bank.

Using a unique data set on language and mathematics test scores for third and fourth graders in eleven 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. Child labor lowers performance on tests of language and mathematics proficiency in every country, 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. (Chapter 5). 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 cause 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.

Methodology

A large amount of literature evaluates the factors that affect children's performance 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 family, F, school, S, and teacher, T, and a measure of the student's ability, A. A measure of the student's time in the labor market, L, can be added to this. The production process can be written

$$Q = f(F, S, T, A, L) \tag{1}$$

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 expenditures per pupil 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 F, S, and T only vary slowly over time, the value of the 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 data sets with measures of the proportion of child time spent in school or at work are unavailable. Because past research suggests that child labor could increase or decrease the productivity of time in secondary or tertiary levels of schooling, and because there are no prior studies on the effect of child labor on

[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.

productivity at the primary level, this study does not make *a priori* predictions on how child labor will affect achievement of young children.[3]

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 third and fourth graders in Latin America. LLECE initially collected data 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 was dropped from the study. Later in this study, missing data on child labor in Cuba will cause that country to be dropped from the analysis as well.

The data set is composed of a stratified sample designed to ensure sufficient observations of public, private, rural (communities with less than 2,500 inhabitants), urban (between 2,500 and 1 million inhabitants), and mega-urban (more than 1 million inhabitants) students in each country. The plan called for data to be obtained from one hundred schools in each country with forty children per school for a total of 4,000 observations per country. Half of the students were to be in the third grade and half in the fourth grade. The stratified samples were designed to be roughly proportional to the populations of five strata: mega-urban public schools, mega-urban private schools, urban public schools, urban private schools, and rural schools. Rural private schools were not included in the sample design.

For budgetary reasons, LLECE used *a priori* geographic exclusions to limit the transportation and time costs of data collection. Exclusion criteria varied from country to country; common criteria were very small schools and those in remote, difficult to access, or

[3] After this study was completed, the authors became aware of a paper by Christopher Heady (2003) that found child labor outside the home lowered student achievement in Ghana.

sparsely inhabited regions. Due to the cost of translating exams, schools with bilingual or indigenous language instruction also were commonly excluded.[4]

The survey used learning tests on language and mathematics with the sample of third and fourth graders and self-applied questionnaires with school principals, teachers, and parents (or legal guardians) of the tested children, as well as the children themselves. In addition, surveyors collected information on the socioeconomic characteristics of the communities.

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, twenty students were randomly selected from third and fourth grade. If there were five or more third- and fourth-grade classes, four classes were chosen, then twenty students were selected from those classes.

An Overview of the Twelve Countries

Children in the third and fourth grades of selected schools in each of the twelve countries were tested on language (Spanish, except for Brazil, whose students were tested on Portuguese) and mathematics. Table 1 presents the average test scores for the two exams by country, along with representative information on each country sample. The language score has a maximum of 19. The average score across all countries is 12, or 63%. 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, more than 53% higher than that of the next highest country. Cuba's academic performance is truly remarkable, given it has the lowest per capita GDP of the twelve countries.[5]

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[4] For a detailed description of the *a priori* exclusions in each country, consult table 6 of the Technical Bulletin of the LLECE.

[5] Official statistics are not available, but CIA estimates of the Cuban GDP per capita in 2000 was $1,700. 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/

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 4% 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 these purposes, 94% of the Cuban children did not answer the question regarding child labor, so the Cuban data cannot be incorporated into the study. Nevertheless, researchers interested in devising policies to improve school efficiency in poor countries would find it useful to study the Cuban case to determine how they generate such superior outcomes.

In the other eleven countries, just under 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 math. 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 scores, except 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 2 presents the unconditional estimates of the mean test scores for language and mathematics by intensity of child labor. Children were asked if, when not in school, they worked outside the home always, occasionally, or never. Their answers create three child labor groups for each country. The test of the difference in means is between those who always work outside the home and those who sometimes or never work.

Across eleven countries and two achievement tests (twenty-two total cases), the pattern never varies. Those 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, averaging 27.5% for languages and 25.0% for mathematics over those who always work. The advantage for occasional child laborers is much smaller, averaging 8.8% in languages and 8.1% in mathematics. The large gap between children who 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.

Regression Analysis

The pattern of unconditional means could be related to other factors that jointly raise child labor and lower test scores, such as 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, available information on school, teacher, and household attributes was added. Because the information was not available for all children, about 50% of the sample was lost. The greatest cause for missing observations was incomplete data on the parents. It should be noted that none of the qualitative results reported were sensitive to the inclusion or exclusion of individual regressors in the model, so the results are not driven by this particular choice of variable.[6]

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[6] The authors also reestimated the model using dummy variable interactions to control for missing observations on ceratain variables. That method resulted in the loss of only 22% of the observations. Qualitative results were not changed.

The summary statistics for the observations in the regressions are reported in table 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, obtained from a survey of their education and years of teaching experience, is included. Efforts also were 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 parental information costs about 10,000 observations, or one-quarter of the sample. The problem of missing observations is most severe in Honduras, Paraguay, Venezuela, and to a lesser extent, Brazil. Because the 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 eleven countries (excluding Cuba) are reported in table 4. The model explains about one-fifth of the variation in test scores across children. Because country dummy variables are included, it can be concluded 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 1% to 2% of the mean test score.

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

Teacher education and experience do not have significant effects in table 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 have strong effects on student outcomes. Having two parents raises language and math scores by 2% to 3%. The average education of the parents or legal guardians has a positive effect, increasing in magnitude as education increases. A household with parental education equal to the sample mean raises test scores by 7% in language and 5% in mathematics. These findings that household attributes strongly influence school performance in Latin America are consistent with those 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.

The most consistent finding in all the countries and for both test scores, by far, 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 2.[7] While the advantage of children who never work relative to those who always work 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 twenty-two possible cases,

[7] The R-square for individual country estimates were of like magnitude to those reported in table 4 for the sample as a whole.

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 (2002) found that virtually all of the positive impact of education on wages is through improved mathematics and language skills. The estimates of this study suggest that the average lost learning as a consequence of being a frequent child laborer is -18.6% in language ability and -15.4% in mathematical ability. The estimated reduction in adult wages as a consequence of being a child laborer, reported by Ilahi et al. (Chapter 5), is -20.3%. Consequently, the percentage loss in cognitive skills attributable to working while in primary school is quite consistent with the corresponding percentage loss in wages later in life.

The estimates reported thus far do not account for possible simultaneity between observed child performance in school and the parents' decision of whether to send the child to work. In Gunnarsson (2003), the authors formally modeled the the choice of whether to send children to work, using variation across countries in truancy age, age at which school starts, whether the country has mandatory preschool and the interaction of these policy measures with the child's age as instruments.[8] The estimated adverse impact of instrumented child labor on test scores was -15.6% for language and -14.4% for mathematics, just slightly smaller than the least squares estimates we report herein. Children who sometimes work scored 12% lower in bothe mathematics and language, much larger than the adverse effects of part-time child labor we report herein. Therefore, the adverse effects of child labor on cognitive achievement found in this study are robust to alternative assumptions about the endogeneity or exogeneity of child labor.

[8] A similar strategy was employed by Angrist and Krueger (1991) to control for endogeneity of years of schooling in their study of returns to education.

Conclusions and Comments

This consistently administered survey of third and fourth graders, their parents, and their teachers in eleven Latin American countries reveals a startling fact—the most consistent predictor of test performance in language and mathematics in terms of sign and significance was whether the child engaged in work outside the home. Children who worked occasionally outperformed those who always worked 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 never worked outside the home was 15% to 19%, even when controlling for parental, teacher and school attributes. Nearly identical results were obtained when controlling for the possble endogeneity of child labor. These 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.

The policy implications are profound. First, there is a cost to having children work while keeping them enrolled in school. Even occasional child workers face a substantial loss of school achievement as a result of their work. As Lam et al. (Chapter 4) demonstrate, child labor is characterized 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 the 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 are 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 1: Representative Characteristics of the Country Samples.

Country	N	Child Labor[a] (%)	Rural[b] (%)	Private[c] (%)	Poor[d] (%)	Test Score Language	Test Score Mathematics
Argentina	4224	34.4	12.4	18.9	21.4	13.5	17.5
Bolivia	4879	56.9	25.8	32.2	35.6	10.8	15.5
Brazil	4374	36.4	16.2	21.7	52.9	13.0	17.2
Chile	4646	45.7	26.5	33.7	46.8	13.0	15.8
Colombia	4306	52.4	28.4	25.0	42.0	11.7	15.4
Cuba	3950	e	33.1	0	4.0	17.1	26.7
Dominican Republic	3729	51.8	33.1	28.2	40.3	9.9	13.1
Honduras	3746	41.6	54.1	11.5	59.8	9.8	12.4
Mexico	5038	43.7	34.7	19.6	24.7	11.4	16.2
Paraguay	4718	29.8	36.0	29.4	23.2	11.4	14.9
Peru	4298	57.1	29.1	22.4	69.1	10.6	12.9
Venezuela	3691	21.4	22.5	21.6	13.0	11.5	11.8
All Countries	51485[f]	40	29.2	22.4	35.9	12.0	15.8

[a]Child indicates 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 to that question.

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

Country	Language Test (Maximum Score = 19)		Mathematics Test (Maximum Score = 32)	
	Unconditional[a]	Conditional[b]	Unconditional[a]	Conditional[b]
Argentina				
Always[c]	12.3	12.3	16.0	16.0
Sometime[d]	13.3**[f]	13.5**	17.6**	17.6**
	(8.1%)[g]	(9.8%)	(10%)	(10%)
Never[e]	14.5**	14.1**	18.9**	18.0**
	(17.9%)	(14.6%)	(18.1%)	(12.5%)
Bolivia				
Always	9.8	9.8	14.5	14.5
Sometime	10.4**	10.3*	15.1*	14.7*
	(6.1%)	(5.1%)	(4.1%)	(1.4%)
Never	12.3**	11.6**	17.2**	15.6**
	(25.5%)	(18.4%)	(18.6%)	(7.6%)
Brazil				
Always	11.4	11.4	14.6	14.6
Sometime	12.1**	11.8	15.9**	15.8**
	(4.3%)	(3.5%)	(8.9%)	(8.2%)
Never	14.0**	13.3**	18.7**	17.8**
	(22.8%)	(16.7%)	(28.1%)	(21.9%)
Chile				
Always	11.6	11.6	13.8	13.8
Sometime	12.6**	12.6**	15.0**	15.0**
	(8.6%)	(8.6%)	(8.7%)	(8.7%)
Never	14.0**	13.6**	17.0**	16.5**
	(20.7%)	(17.2%)	(23.2%)	(19.6%)
Colombia				
Always	10.3	10.3	14.2	14.2
Sometime	11.5**	11.7**	15.6**	15.8**
	(11.7%)	(13.6%)	(9.9%)	(11.3%)
Never	12.8**	12.6**	16.4**	16.1**
	(24.3%)	(22.3%)	(15.5%)	(13.4%)

Country	Language Test (Maximum Score = 19)		Mathematics Test (Maximum Score = 32)	
	Unconditional[a]	Conditional[b]	Unconditional[a]	Conditional[b]
Dominican Republic				
Always	9.5	9.5	12.6	12.6
Sometime	9.7	9.5	13.3**	13.3*
	(2.1%)	(0%)	(5.6%)	(5.6%)
Never	11.1**	10.6**	13.8**	13.1
	(16.8%)	(11.6%)	(9.5%)	(4.0%)
Honduras				
Always	9.1	9.1	11.8	11.8
Sometime	9.7**	9.4	12.6**	11.0
	(6.6%)	(3.3%)	(6.8%)	(-6.8%)
Never	11.8**	11.9**	14.6**	13.2*
	(29.7%)	(30.8%)	(23.7%)	(11.9%)
Mexico				
Always	9.6	9.6	13.8	13.8
Sometime	10.6**	10.7**	15.1**	15.4**
	(10.4%)	(11.5%)	(9.4%)	(11.6%)
Never	12.5**	11.8**	17.7**	17.1**
	(30.2%)	(22.9%)	(28.3%)	(23.9%)
Paraguay				
Always	11.2	11.2	13.9	13.9
Sometime	11.8**	11.8	15.5**	15.4
	(5.4%)	(5.4%)	(11.5%)	(10.8%)
Never	13.1**	13.1**	17.3**	18.0**
	(17.0%)	(17.0%)	(24.5%)	(29.5%)
Peru				
Always	9.1	9.1	11.6	11.6
Sometime	10.1**	9.7**	11.9	11.8
	(11.0%)	(6.6%)	(2.6%)	(1.7%)
Never	12.2**	10.7**	14.9	13.4**
	(34.1%)	(17.6%)	(28.4%)	(15.5%)

Country	Language Test (Maximum Score = 19)		Mathematics Test (Maximum Score = 32)	
	Unconditional[a]	Conditional[b]	Unconditional[a]	Conditional[b]
Venezuela				
Always	10.0	10.0	12.2	12.2
Sometime	10.9**	10.5	13.0*	12.9
	(9.0%)	(5.0%)	(6.6%)	(5.7%)
Never	11.5**	11.3**	14.5**	13.7**
	(15.0%)	(13.0%)	(18.9%)	(12.3%)
All Countries				
Always	10.2	10.2	13.6	13.6
Sometime	11.1**	10.9**	14.7**	14.4**
	(8.8%)	(6.9%)	(8.1%)	(5.9%)
Never	13.0**	12.1**	17.0**	15.7**
	(27.5%)	(18.6%)	(25.0%)	(15.4%)

[a]Simple mean test score over all children in the child labor group in the country.
[b]Based on coefficients of dummy variables for "Sometime" and "Never" from country-specific regressions comparable to the specifications reported in Table 4. The regressions also included all the school, teacher, and household factors included in Table 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]Child never works outside the home.
[f]Indicates difference in mean test score from the "always working" group is significant at the .05(*) or .01(**) level of significance.
[g]Percentage difference relative to children who always work outside the home when not in school.

Table 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
Never	Dummy variable indicating if child never works outside the home	0.43	0.49
School Factors			
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	31.0	12.4
Teacher Factors			
Education	Education level of the teacher, indicated by an index in which 0=none, 1=secondary, 3=tertiary	1.45	0.56
Experience	Years the teacher has been teaching	13.8	8.9
Household Factors			
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 in which 1=primary incomplete, 2= primary complete, 3=secondary incomplete, 4= secondary complete, 5=tertiary incomplete, 6= tertiary complete	2.74	1.63

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

Table 4: Pooled Educational Production Function Estimation.

	LANGUAGE	MATHEMATICS
CHILD LABOR		
Sometime	0.70^{**}	0.80^{**}
	(9.11)	(7.12)
Never	1.85^{**}	2.06^{**}
	(24.6)	(18.7)
SCHOOL FACTORS		
Rural	-0.91^{**}	-0.39^{**}
	(12.1)	(3.63)
Public	-0.85^{**}	-1.77^{**}
	(11.1)	(15.7)
Single Grade	-0.10	-0.30^{*}
	(0.98)	(2.08)
Pupils/Classroom	0.00	0.00
	(1.07)	(0.63)
TEACHER FACTORS		
Education	0.31	-0.16
	(1.15)	(0.42)
Education^2	-0.04	0.15
	(0.40)	(1.04)
Experience	-0.00	0.00
	(0.39)	(0.25)
HOUSEHOLD FACTORS		
Two Parents	0.23^{**}	0.38^{**}
	(3.12)	(3.61)
Head Education	0.18^{**}	-0.07
	(2.54)	(0.67)
$(\text{Head Education})^2$	0.05^{**}	0.12^{**}
	(4.53)	(7.29)
COUNTRY DUMMIES	Included	Included
R^2	0.21	0.18
N	18375	18373
Mean of dependent variable	11.6	14.9

t-statistics in parentheses.
*indicates significance at the .05 confidence level.
**indicates significance at the .01 confidence level.

Table

Variable	Child Labor Exogenous[a] Mathematics	Language	Child Labor Endogenous[b] Mathematics	Language
Sometime	-1.519*	-1.284*	-1.842*	-1.390*
	(0.080)	(0.050)	(0.139)	(0.090)
Proportion[c]	-0.099	-0.109	-0.120	-0.118
Often	-2.474*	-2.058*	-2.218*	-1.845*
	(0.090)	(0.057)	(0.391)	(0.346)
Proportion	-0.161	-0.174	-0.144	-0.156
Child				
Age	0.071*	0.079*	0.090*	0.100*
	(0.024)	(0.016)	(0.025)	(0.020)
Boy	0.775*	-0.300*	1.000*	-0.112*
	(0.068)	(0.043)	(0.073)	(0.049)
No Preschool	-0.532*	-0.326*	-0.505*	-0.312*
	(0.084)	(0.053)	(0.081)	(0.052)
Parents/Household				
Parent Educ	0.468*	0.356*	0.380*	0.275*
	(0.029)	(0.018)	(0.035)	(0.021)
Books at Home	0.866*	0.549*	0.735*	0.449*
	(0.052)	(0.032)	(0.053)	(0.034)
Teacher				
Male	-0.436*	-0.546*	-0.358*	-0.484*
	(0.029)	(0.059)	(0.108)	(0.063)
Teacher Educ	-0.624*	0.090	-0.575*	0.141*
	(0.075)	(0.048)	(0.087)	(0.054)
School				
Spanish Enr/100	-0.031*	0.025*	-0.039*	0.016*
	(0.007)	(0.005)	(0.007)	(0.006)
Inadequacy	-0.421*	-0.342*	-0.359*	-0.289*
	(0.039)	(0.024)	(0.043)	(0.023)
Math/week (Spanish/week)	0.008	0.008	-0.004	0.003
	(0.014)	(0.007)	(0.015)	(0.008)
Community				
Urban	0.331*	0.086	0.104	-0.091*
	(0.087)	(0.054)	(0.077)	(0.057)
Rural	-1.046*	-1.240*	-1.117*	-1.266*
	(0.106)	(0.066)	(0.102)	(0.064)
Constant	15.673*	10.143*	15.882*	10.373*
	(0.387)	(0.202)	(0.372)	(0.229)
R^2	0.133	0.171	0.129	0.147
N	28939	34306	28939	34306