Child Labor and School Achievement in Latin America

Victoria Gunnarsson, Peter F. Orazem, and Mario A. Sánchez

Child labor's effect on academic achievement is estimated using unique data on third and fourth graders in nine Latin-American countries. Cross-country variation in truancy regulations provides an exogenous shift in the ages of children normally in these grades, providing exogenous variation in the opportunity cost of children's time. Least squares estimates suggest that child labor lowers test scores, but those estimates are biased toward zero. Corrected estimates are still negative and statistically significant. Children working 1 standard deviation above the mean have average scores that are 16 percent lower on mathematics examinations and 11 percent lower on language examinations, consistent with the estimates of the adverse impact of child labor on returns to schooling.

About one of eight children in the world is engaged in market work. Despite general acceptance that child labor is harmful and despite international accords aimed at its eradication, progress on lowering the incidence of child labor has been slow. Although often associated with poverty, child labor has persisted in some countries that have experienced substantial improvements in living standards. For example, Latin America, with several countries in the middle- or upper-middle-income categories, still has child labor participation rates that are similar to the world average.

Countries have adopted various policies to combat child labor. Most have opted for legal prohibitions, but these are only as effective as the enforcement. As many child labor relationships are in informal settings within family enterprises, enforcement is often difficult. Several countries, particularly in Latin America, have initiated programs that offer households an income transfer in exchange for keeping children in school and out of the labor market.

Victoria Gunnarsson is a research officer in the Fiscal Affairs Department at the International Monetary Fund; her email address is vgunnarsson@imf.org. Peter F. Orazem is a professor at Iowa State University; his email address is pfo@iastate.edu. Mario A. Sánchez is a social development specialist at the Inter-American Development Bank; his e-mail address is mariosan@iadb.org. The authors thank Wallace Huffman, Robert Mazur, three referees, the editor, and seminar participants at Iowa State and Minnesota for numerous comments and suggestions.

THE WORLD BANK ECONOMIC REVIEW, VOL. 20, NO. 1, pp. 31–54 doi:10.1093/wber/lhj003
Advance Access publication March 2, 2006

Presumably, governments invest resources to lower child time in the labor market in anticipation that the child will devote more time to the acquisition of human capital. The government's return will come from higher average earnings and reduced outlays for poverty alleviation when the child matures. However, despite a huge acceleration in the research on child labor, there is surprisingly little evidence that relates child labor to schooling outcomes in developing countries.[1] Most children who work are also in school, suggesting that child labor does not lower school attainment. Additionally, studies that examine the impact of child labor on test scores have often found negligible effects, although most of these are in industrial country contexts. More recently, Heady (2003) and Rosati and Rossi (2003) have found some evidence that child labor lowers primary school test scores in developing countries.

This article builds on these last two studies by examining the link between child labor and school achievement in nine countries in Latin America. This article benefits from more detailed data sets that allow controls for child, household, school, and community variables, and it uses an empirical strategy that controls for the likely endogeneity of child labor. The results are consistent: in all nine countries, child labor lowers performance on the tests of language and mathematics proficiency, even when controlling for school and household attributes and for the joint causality between child labor and school outcomes. To the extent that lower cognitive attainment translates into lower future earnings, as argued by Glewwe (2002), these results suggest that there is a payoff in the form of higher future earnings from investing in lowering the incidence of child labor.

I. Literature Review

Most studies that analyze the relationship between time at work and school attainment have focused on high-school or college students in industrial countries.[2] These studies have generally found little evidence that part-time work combined with schooling affects school achievement. When adverse effects are found, they are apparent only at relatively high work hours. Important exceptions include recent studies by Tyler (2003) and Stinebrickner and Stinebrickner (2003) that found that after controlling for the likely endogeneity of child labor, working while in school led to much larger implied declines in high-school math scores and in college grade point averages than had been found previously. Post and Pong (2000) also found a negative association between

1. Two excellent recent reviews of the recent literature are by Basu and Tzannatos (2003) and Edmonds and Pavcnik (2005).

2. D'Amico (1984), Ehrenberg and Sherman (1987), Howard (1998), Lillydahl (1990), Singh (1998), Stern (1997), and Singh and Ozturk (2000).

work and test scores in samples of eight graders in many of the 23 countries they studied.[3]

There are several reasons why the experience of older working students may differ from that of young children working in developing countries. Young children may be less physically able to combine work with school, so that young working children may be too tired to learn efficiently in school or to study afterwards. Children who are tired are also more prone to illness or injury that can retard academic development. It is possible that working at a young age disrupts the attainment of basic skills more than it disrupts the acquisition of applied skills for older students. School and work, which may be complementary activities once a student has mastered literacy and numeracy, may not be compatible before those basic skills are mastered.

Past research on the consequences of child labor on schooling in developing countries has concentrated on the impact of child labor on school enrollment or attendance. Here the evidence is mixed. Patrinos and Psacharopoulos (1997) and Ravallion and Wodon (2000) found that child labor and school enrollment were not mutually exclusive and could even be complementary activities. However, Rosenzweig and Evenson (1977) and Levy (1985) found evidence that better-developed child labor markets lowered school enrollment. There is stronger evidence that child labor lowers time spent in human capital production, even if it does not lower enrollment. Psacharopoulos (1997) and Sedlacek and others (forthcoming) reported that child labor lowered years of school completed, and Akabayashi and Psacharopoulos (1999) discovered that child labor lowered study time.

Nevertheless, school enrollment and attendance are not ideal measures of the potential harm of child labor on learning because they are merely indicators of the time input into schooling and not the learning outcomes. Even if child labor lowers time in school, it may not hinder human capital production if children can use their limited time in school efficiently. This is particularly so if schools are of such poor quality that not much learning occurs in any case. By contrast, the common finding that most working children are enrolled in school may miss the adverse consequences of child labor on learning if child labor is not complementary to the learning process at the lower grades.

A more accurate assessment of the impact of child labor on human capital production requires the measures of learning outcomes, such as test scores, rather than education inputs, such as time in school, to determine whether child labor limits or enhances human capital production. Moreover, evidence suggests that cognitive skills, rather than years of schooling, are the fundamental determinants of adult wages in developing countries (Glewwe 1996, Moll 1998).

3. The study included several developing countries, including Colombia, Iran, South Africa, Thailand, and the Philippines, which had the largest estimated negative effects of child labor on school achievement. However, the estimates do not control for school attributes or possible joint causality between school achievement and child labor.

Therefore, identifying the impact of child labor on school achievement will yield more direct implications for child labor's longer-term impacts on earnings and poverty status later in the child's life.

Direct evidence of the impact of child labor on primary school achievement is rare. Heady (2003) found that child work had little effect on school attendance but a substantial effect on learning achievement in reading and mathematics in Ghana. Rosati and Rossi (2003) reported that in Nicaragua and Pakistan, more hours of child labor are associated with poorer test scores. Both of these studies have weaknesses related to data limitations. Heady treated child labor as exogenous, but it is plausible that parents send their children to work in part because of poor academic performance. Rosati and Rossi had no information on teacher or school characteristics, although these are likely to be correlated with the strength of local child labor markets.

This study makes several important contributions to knowledge of the impact of child labor on schooling outcomes in developing countries. It shows how child labor affects test scores in nine developing countries, greatly expanding the scope of existing research. Because the same examination was given in all countries, the study can illustrate how the effect of child labor on cognitive achievement varies across countries that differ greatly in child labor incidence, per capita income, and school quality. Because the countries also differ in the regulation and enforcement of child labor laws, cross-country variation in schooling ages and truancy laws can provide plausible instruments for endogenous child labor. Finally, because the data set includes a wealth of information on parent, family, community, and school attributes, the impact of child labor on schooling outcomes can be estimated while holding fixed other inputs commonly assumed to explain variation in schooling outcomes across children.

The results are consistent. Child labor lowers student achievement in every country. The conclusions are robust to alternative estimation procedures and specifications. The inescapable conclusion is that child labor has a significant opportunity cost in the form of forgone human capital production, a cost that may not be apparent when looking only at enrollment rates for working children.

II. Empirical Model

Ben Porath (1967) laid out the classic model of human capital investments over the life cycle. There are diminishing marginal returns to time in school because of concavity in the human capital production process and because the opportunity cost of allocating time to further skill acquisition increases as skills are accumulated. In addition, finite life spans limit the length of time to capture returns from schooling as age increases, further decreasing the marginal returns to time in school as age rises. All of these factors suggest that time invested in human capital production will decrease as an individual ages. However, early in life, children may specialize in schooling if the present value of the return is sufficiently high relative to its current marginal cost.[4]

Of interest here is the tradeoff parents face in deciding whether a child should specialize in schooling or should divide time between school and work. By age t, the child has completed E_t years of schooling. In addition, the child has matured for t years. The opportunity cost of a child's school time is assumed to rise with E_t and t and is also a function of local labor market conditions Z_t. The returns to time in school will depend on how much the child is expected to learn, Q_t. A vector of observable parent, home, school, and community variables, H_t, may affect tastes for child labor as well as the productivity of child time in school through Q_t. The child's labor supply function will be of the form

$$C_t = c(E_t, t, Z_t, Q_t, H_t, \varepsilon_t) \tag{1}$$

where ε_t is a random error.

The human capital production process is assumed to depend on past human capital accumulations, current factors that would make the child's time in school more productive, and the time spent in school. Letting Q_t be an observable measure of cognitive skills produced in school, the human capital production process will be of the form

$$Q_t = q(E_t, t, C_t, H_t, \eta_t) \tag{2}$$

where η_t is a component of cognitive ability that the parents can observe but not the econometrician.

Because the decision on whether or how much the child works is based in part on the parents' knowledge of η_t, and because student outcomes are influenced by child labor, $Var(\varepsilon_t, \eta_t) \neq 0$, and ordinary least squares estimation of equation (2) will be biased. Short of a randomized experiment that assigns children into working and non-working groups, the best candidate to resolve the problem will be to find variables that shift the probability that a child works but do not directly affect child learning in school. Needed are variables that alter the local labor market for child labor, Z_t, to provide exogenous shifts in the child labor equation in estimating equation (2).

Factors Shifting the Probability of Child Labor

Elements of the vector Z_t are required that alter the local labor market for children but do not affect test scores. Because the probability of working rises

4. The main predictions are not altered if leisure is added to the model. It will still be optimal to invest more intensively in human capital early in life and to decrease investment intensity with age. In addition, because the cost of leisure is the value of work time, individuals will consume the least leisure when wages are highest. In the application here, children will consume less leisure as they age, and so older children will still be expected to work more than younger children. Heckman (1976) presented a detailed model of human capital investment, leisure demand, and consumption over the life cycle. Huffman and Orazem (2006) present a much-simplified model that generates the predictions discussed in the text.

with age, factors that alter the age at which a child would normally be in a given grade will also affect the probability that the child will be working. In Latin America, the age at which children are expected to start school varies across countries from 5 to 7 years of age. The age at which a child may legally leave school also varies from 12 to 16 years of age. As a consequence, children must attend school as few as 5 years in Honduras to as many as 10 years in Peru.

These differences in laws regulating school attendance and child labor alter the age at which children would normally enter grades 3 and 4 and thus the opportunity costs of being in those grades. Children starting school earlier will be younger at grade 3 and more likely to attend school full time without working. Third and fourth graders in countries with the lowest working ages are more likely to appear legal, even if they are under 12 years of age. Therefore, children in countries with low truancy ages will be more likely to be working while attending school.

An alternative measure of the opportunity cost of attending school would be the local market wage for children. Because most child labor is unpaid work for family enterprises, however, market wages would not adequately capture the value of time outside of school even if such information were available. In their place is used the presumed upward relationship between the marginal productivity of child labor and the child's age, assumed to be driven largely by physical stature.[5] Interactions between measures of a country's school starting age or truancy age and a child's age are used to capture exogenous variation across countries in the probability that third and fourth graders work. These shifts in the net return to time in school provide the needed exogenous shift in C.[6]

Within countries the largest source of variation in demand for child labor occurs across rural and urban areas. There are more uses for child labor in rural markets, and so labor force participation rates are higher for rural children than for urban children in all the countries in this study. That source of variation is captured with interactions between child age and a dummy variable indicating rural residence for boys and girls.

How these elements of Z_t affect the probability of engaging in child labor is illustrated in figures 1–3.

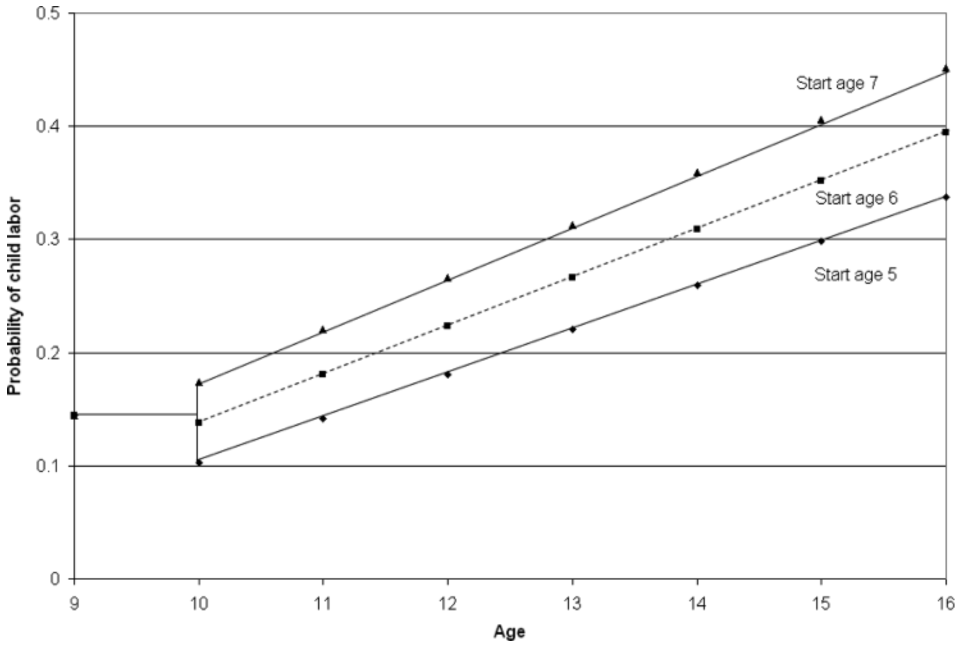
Factors Affecting School Outcomes

Estimation of equation (2) follows the educational production function literature in that Q is measured by test scores that are explained by variables characterizing the student's parents, household, teacher, school, and community

5. Rosenzweig (1980) found that in a sample of adults, wages for day labor in India were primarily driven by stature and not by acquired education. Wage patterns reported by Ray (2000) for boys and girls in Pakistan and Peru suggest rising opportunity costs of child time as age increases.

6. Angrist and Krueger (1991) used variation in compulsory school starting ages across states to instrument for endogenous time in school in their analysis of returns to schooling using U.S. Census data. Tyler (2003) used variation in state child labor laws to instrument for child labor in his study of U.S. high-school test scores. This study began with a large number of interactions, but the resulting variables were highly collinear, and so a parsimonious subset of the fuller specification was used.

FIGURE 1. Predicted Child Labor by Child Age and School Starting Age



Source: Authors' simulations based on results in table 2, column 1.

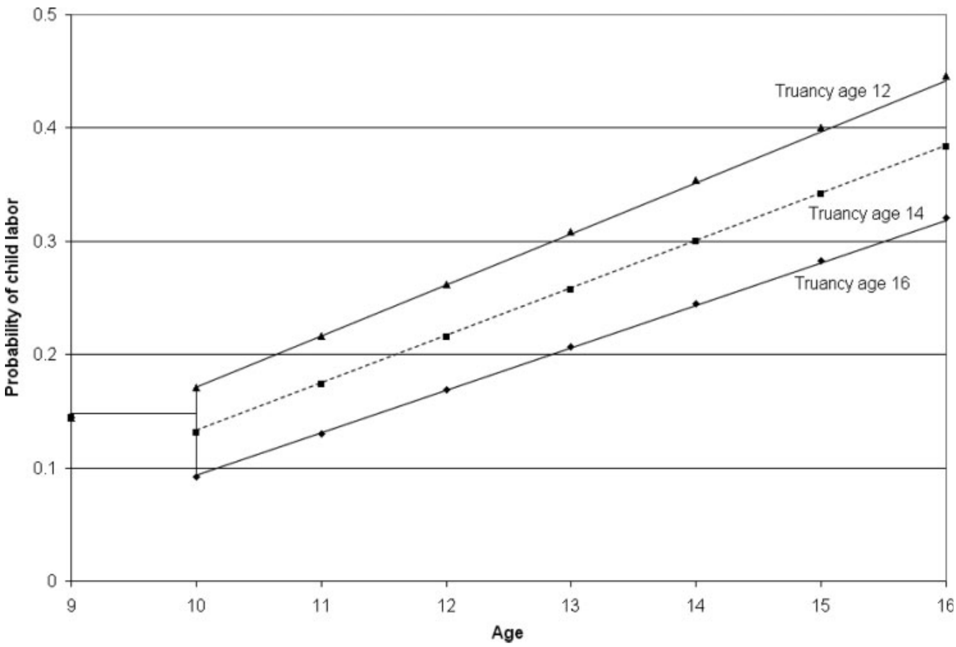
(Hanushek 1995). Measures used include most of those that have been found to be important in developing country settings (Hanushek 1995, Kremer 1995).

Estimates of educational production functions are subject to numerous biases.[7] Among the most commonly discussed is the lack of adequate control for the student's innate ability.[8] Many studies have attempted to correct for the problem by using two test scores taken at different times. If ability has an additive effect on school achievement, the difference between the two output measures will be purged of the ability effect. The data for the current study include only tests taken at one point in time, so the differencing option is not available. However, there are reasons why undifferenced data may yield satisfactory or even preferred estimates to the differenced data. As Glewwe (2002) argued, if measures of H_t vary slowly over time, the value of the differenced measure of achievement is minimal. This is more likely to be true at the earliest stages of schooling, when there is less variation in curriculum, educational materials, or teacher training. Furthermore, the use of parental attributes such

7. See Glewwe (2002) for a comprehensive review of the problems associated with estimating educational production functions.

8. Ability bias has also been the subject of numerous studies estimating returns to schooling. The consensus is that the bias is small (Card 1999). If earnings and cognitive skills are closely tied, as argued by Glewwe (2002), the role of ability bias should be small in educational production estimates also.

FIGURE 2. Predicted Probability of Child Labor by Child Age and School Leaving Age



Source: Authors' simulations based on results in table 2, column 1.

as education and income should partially control for inherited ability. Finally, if there is considerable measurement error in estimates of Q_t, the level of Q_t may be measured more reliably than the change in Q_t. In any event, the results of the production function estimation in this study should be interpreted as cumulative as of grade 3 or 4 rather than the additional learning obtained in that grade.

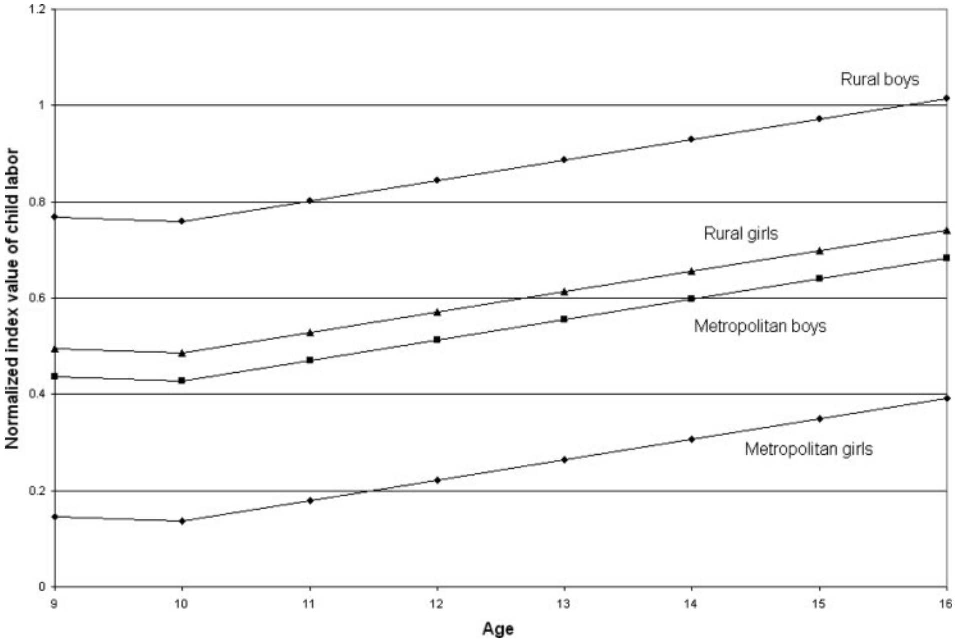
III. DATA

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 third and fourth graders in Latin America. LLECE initially collected data in 13 countries, but the required information for the regression analysis for this study was available only for nine countries: Argentina, Bolivia, Brazil, Chile, Colombia, Dominican Republic, Honduras, Paraguay, and Peru.[9]

The data set is composed of a stratified sample designed to ensure sufficient observations of public, private, rural, urban, and metropolitan students in each

9. Costa Rica was included in the initial data collection, but LLECE dropped those data because of consistency problems. Cuba was excluded because of missing data on child labor. Mexico and Venezuela lacked required information on child age.

FIGURE 3. Predicted Child Labor Probability by Child Age, Gender, and Region



Source: Authors' simulations based on results in table 2, column 1.

country. Data were collected on 40 children from each of 100 schools in each country for a total of 4,000 observations per country. Half of the students were in the third grade and half in the fourth grade. For budgetary reasons LLECE had to use a priori geographic exclusions to limit the transportation and time costs of data collection. Very small schools with too few third and fourth graders and schools in remote, difficult to access, or sparsely inhabited regions were excluded. Because of the cost of translating examinations, schools with bilingual or indigenous language instruction were also excluded.[10] As the excluded schools would cater to relatively more disadvantaged populations, our results should be viewed as applying to school populations that are less rural, from more majority ethnic groups, and somewhat more advantaged than average for all Latin-American children.

Test Scores

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

10. For a detailed description of the a priori exclusions in each country, see Table III.6 of the Technical Bulletin of the LLECE.

community. A description of the variables used in the analysis is provided in appendix table A-1, and summary statistics are reported in appendix table A-2.[11]

All children were tested in mathematics, and all were tested in Spanish except the Brazilian children who were tested in Portuguese. The tests and questionnaires were given only to children who attend school, so no information was obtained on children who are not in school. Therefore, the results can be applied to enrolled children only. If working children who perform most poorly in school drop out to work full time, the estimate of the consequences of child labor on schooling outcomes may miss some of those most harmed by child labor while including children who can work and still perform well in school. However, 95 percent of children aged 9–11 are enrolled in Latin America, so the bias is likely to be modest.[12] In settings where primary enrollment rates are much lower, the bias could be substantial, however.

Child Labor

Child labor is measured by children's responses to a question asking whether they are engaged in work outside the home.[13] The concentration on paid work outside the home avoids some definitional problems related to distinguishing unpaid work for home enterprise from household chores. However, it is also apparent in the application that child labor in the home does not have the same apparent negative consequences on student achievement as does work outside the home.

A comparison of the intensity of child labor participation rates in nine countries for children who report that they work inside or outside the home and average language and mathematics test scores shows an unvarying pattern (table 1).[14] Children who work only some of the time outperform those who work often. Children who almost never work outperform those who work sometimes or often. The differences are almost always statistically significant. The advantage is large for children who almost never work over those who often work, averaging 22 percent on the mathematics examination and 27 percent on the language

11. For some reason, language scores were reported for 2 percent fewer students than were mathematics scores. The missing scores appear to be due to random reporting errors, as there were no large differences between the sample means of the group taking the mathematics and language tests. The means are reported from the sample taking the mathematics examination.

12. Sedlacek and others (2005) presented data on enrollment by age for 18 Latin-American countries. Even for the poorest quintile of children, enrollment rates are more than 90 percent for children aged 9–11.

13. As pointed out by a referee, it would be better to have information on hours of work rather than these more-vague measures of work intensity. The instrumental variables procedure described later is an attempt to correct for biases because of measurement error in child labor.

14. The averages are reported for the subset of countries for which data were available on both language and mathematics test scores and for which responses could be matched for working inside and outside the home. Only partial information was available for Mexico and Venezuela, but the pattern of average test scores for children working outside the home in Mexico and Venezuela was the same—children working more outside the home had significantly lower average test scores. Data limitations prevented generating the corresponding average test scores for children working inside the home for those two countries.

TABLE 1. Unconditional Average Language and Mathematics Test Scores, by Country and Type and Level of Child Labor for Children Aged 6–18 Years Old

Country	Working Outside the Home: Language Test Scores (Maximum Score = 19)	Working Outside the Home: Mathematics Test Scores (Maximum Score = 32)	Working Inside the Home: Language Test Scores (Maximum Score = 19)	Working Inside the Home: Mathematics Test Scores (Maximum Score = 32)
Argentina				
Often	12.0	15.7	13.9	17.9
Sometimes	13.0 (8.3)**	17.2 (9.6)**	14.3 (2.9)*	18.6 (3.9)*
Almost never	14.3 (19.2)**	18.4 (17.2)**	14.7 (5.8)*	19.9 (11.2)**
Bolivia				
Often	9.7	14.2	11.2	15.9
Sometimes	10.1 (4.1)*	14.7 (3.5)	11.2 (0.0)	16.0 (0.6)
Almost never	11.3 (16.5)**	15.1 (6.3)**	11.8 (5.4)	17.2 (8.2)*
Brazil				
Often	11.2	14.4	13.0	16.9
Sometimes	11.7 (4.3)*	15.5 (7.6)**	13.4 (3.1)**	18.0 (6.5)**
Almost never	13.5 (20.5)**	17.9 (24.3)**	13.0 (0.0)	17.5 (3.6)
Chile				
Often	11.3	13.3	13.4	16.7
Sometimes	12.1 (7.1)**	14.8 (11.3)**	13.7 (2.2)	17.3 (3.6)*
Almost never	13.5 (19.5)**	16.1 (21.1)**	14.0 (4.5)	17.7 (6.0)*
Colombia				
Often	9.9	13.9	11.7	15.7
Sometimes	11.1 (12.1)**	15.3 (10.1)**	12.2 (4.3)*	15.8 (0.6)
Almost never	12.4 (25.3)**	15.9 (14.4)**	12.2 (4.3)	16.1 (2.5)
Dominican Republic				
Often	9.6	12.8	10.3	13.2
Sometimes	9.6 (0.0)	13.2 (3.1)	10.8 (4.8)	13.8 (4.5)
Almost never	10.8 (12.5)**	13.2 (3.1)	10.2 (–1.0)	12.4 (–6.1)

(Continued)

TABLE 1. Continued

Country	Working Outside the Home		Working Inside the Home	
	Language Test Scores (Maximum Score = 19)	Mathematics Test Scores (Maximum Score = 32)	Language Test Scores (Maximum Score = 19)	Mathematics Test Scores (Maximum Score = 32)
Honduras				
Often	8.9	11.7	10.2	13.2
Sometimes	9.4 (5.6)*	12.3 (5.1)**	10.0 (–2.0)	12.7 (–3.8)
Almost never	11.6 (30.3)**	14.5 (23.9)**	9.5 (–6.9)	10.8 (–10.6)
Paraguay				
Often	10.2	12.9	12.5	16.4
Sometimes	11.3 (10.8)**	14.9 (15.5)**	13.5 (8.0)**	17.9 (9.1)**
Almost never	12.1 (18.6)**	16.4 (27.1)**	11.1 (–11.2)	14.8 (–9.8)
Peru				
Often	8.7	11.0	10.6	12.7
Sometimes	9.5 (9.2)**	11.2 (1.8)	11.0 (3.8)**	13.5 (6.3)**
Almost never	11.2 (28.7)**	12.9 (17.3)**	10.6 (0.0)	13.0 (2.4)
All countries				
Often	9.9	13.1	11.7	15.4
Sometimes	10.8 (9.0)**	14.2 (8.4)**	12.2 (4.3)**	16.1 (4.5)**
Almost never	12.6 (27.3)**	16.0 (22.1)**	12.5 (6.8)**	16.5 (7.1)**

*Difference from often working group significant at the 0.05 confidence level.

**Difference from often working group significant at the 0.01 confidence level.

Note: Results are the simple mean test score over all children in the child labor group in the county. Numbers in parentheses are the percentage difference relative to children who often work outside the home when not in school. For definitions of "often," "sometimes," and "almost never," see table A-1.

Source: Authors' computations based on data from the 1997 survey by the Latin-American Laboratory of Quality of Education, as described in the text; UNESCO (2002).

examination. The test advantage for occasional child laborers is smaller but still significant at 8.4 percent for mathematics and 9 percent for languages.

Children were asked a similar question about how intensively they worked inside the home. It seems that working inside the home is less costly for human capital development in schools. Across all countries, those who work often inside the home have average test scores only 7 percent lower than those who almost never work inside the home and only 4 percent lower than those who sometimes work inside the home. The test score gaps for those working outside the home were considerably larger. Furthermore, in only three of the nine countries were average test scores significantly higher for children almost never working inside the home relative to those often working inside the home. In three other countries, those often working inside the home had higher average test scores than did those rarely working inside the home.

Nevertheless, there is a more basic reason for not analyzing the implications of working inside the home on student achievement: more than 95 percent of students reported working inside the home sometimes or often, with nearly identical incidence of work reported for girls and boys and for urban and rural children. This lack of meaningful variation means that the pattern of test scores against work intensity inside the home is unlikely to be reliable. In fact, attempted empirical models could not distinguish statistically between children who did and those who did not work inside the home—everyone was predicted to participate in household labor. It is possible that work inside the home is damaging to schooling outcomes, but our data lack sufficient variation in measured household work to capture the effect. For these reasons, we concentrate our analysis on child labor outside the home.

Exogenous Variables

The presumed positive relationship between age and the value of child time working outside the home is used to identify the child labor equation. This relationship varies across urban and rural areas and between boys and girls. It also appears to shift as children reach 10 years of age. This effect is allowed with a spline defined as follows. A dummy variable, d10, takes the value of 1 for children under 10 years of age and 0 otherwise. For children aged 10 and older, the age effect is captured by interactions between (1 – d10) and age.

The countries included in the data differ in their legal regulations governing the age at which children enter school and when they can leave school. Information on compulsory schooling laws for each country was obtained from the UNESCO (2002). In the empirical specification, these laws shift the age–child labor relationship beyond age 10, using interaction terms of the form AGE (1 – d10) LAGE, where LAGE is the legal age of school entry or school exit.[15]

15. This is a more parsimonious specification than the one with all possible interaction terms. In particular, separate coefficients on the dummy variable (1 – d10) and their interactions with age, gender, and rural residence did not add to the explanatory power of the child labor equation.

The child's value of time in school will depend on how much the child can learn. This will depend on home attributes that are complementary to child time in school, such as books and parental education, and on the quality of the school. Most of these measures are self-explanatory. However, some of the school variables merit comment. The measure of the classroom environment, inadequacy, is a weighted average of several measures of poor school infrastructure and supplies. Teachers were asked the extent to which they judged classroom lighting, temperature, hygiene, security, acoustics, and textbooks to be inadequate. The weighted sum of the responses is used as the aggregate index of school shortcomings, where the weights were taken as the first principal component from a factor analysis of the teachers' responses. The number of Spanish- or Portuguese-speaking students is included as a measure of the cost of providing schooling services. As the number of nonnative speakers of the language of instruction increases, resources must be diverted to second-language instruction, potentially limiting school productivity.

IV. Econometric Strategy

The results in table 1 suggest a strong negative effect of child market labor on school achievement, but the effect may be in the reverse direction—poor schooling outcomes leading to child labor. The direction of this bias is difficult to predict. The most plausible is that poor school performers are sent to work so that the least squares coefficient on child labor will be biased downward. However, both Tyler (2003) and Stinebrickner and Stinebrickner (2003) found biases in the opposite direction for older students, with better students more likely to work. Measurement error in the self-reported incidence of child labor could also bias the estimated coefficient of child labor on schooling outcomes. The cumulative direction of these sources of bias cannot be established, but both simultaneity and measurement error can be handled by the use of plausible instruments that alter the probability of engaging in child labor without directly affecting test scores.

The first step in the estimation process is to predict child labor. The categorical measure of child market work includes 0 (almost never work), 1 (sometimes work), and 2 (often work). Equation (1) was estimated with an ordered probit specification, using child, parent, school, and community variables to explain variation in market work. Predicted child labor from equation (1) is used as the measure of C in estimating equation (2). This two-stage estimation leads to consistent, but inefficient estimates of the parameters of the achievement equation. A bootstrapping method is used to correct for the inefficiency in the estimators in which 100 samples with replacement are drawn from the original data, subjected to the ordered probit estimation and then inserted into the second-stage achievement equation to simulate the sampling variation in the estimates. The bootstrap standard errors are reported for the test score equations.

V. Determinants of Child Labor

Estimates from the probit child labor supply equation, reported in table 2, are needed to identify the effect of child labor on test scores but are also of interest in their own right. The estimation uses the dependent variables reported in table 1 except that data for Mexico and Venezuela are dropped because child's age was not reported. Because the two samples are not identical, separate estimates are reported for the samples of children taking the mathematics and language examinations. The coefficients on the age-interacted variables differ somewhat across the two samples, but the overall relationship between age and child labor is similar between the two samples. The other coefficient estimates are similar across the two samples.

Boys are more likely than girls to work outside the home, and rural boys and girls work more than their urban counterparts, who in turn work more than their metropolitan counterparts. Children of more-educated parents and

Table 2. Ordered Probit Regression Results on Child Labor

Variable	Mathematics Test Scores	Language Test Scores
Exogenous variables		
Child		
Age	0.048 (0.009)**	−0.014 (0.009)
Boy	0.291 (0.036)**	0.163 (0.037)**
No preschool	−0.016 (0.019)	0.029 (0.019)
Parents/household		
Parent education	−0.065 (0.007)**	−0.046 (0.008)**
Books at home	−0.080 (0.012)**	−0.071 (0.012)**
School		
Spanish enrollment/100	−0.004 (0.002)**	−0.005 (0.002)**
Inadequate supply	0.062 (0.009)**	0.065 (0.009)**
Math/week (Spanish/week)	−0.014 (0.004)**	−0.010 (0.003)**
Community		
Rural	0.350 (0.033)**	0.290 (0.034)**
Urban	0.197 (0.033)**	0.121 (0.031)**
Instruments		
Boy×rural	−0.019 (0.045)	0.144 (0.045)**
Boy×urban	−0.062 (0.043)	0.103 (0.044)**
Age×compulsory start (1 − d10)	0.004 (0.001)**	0.002 (0.001)*
Age×compulsory end (1 − d10)	−0.002 (0.000)**	0.000 (0.001)
LL	−21,623.743	−21,179.099
Pseudo R^2	0.034	0.034
Number of observations	20,699	20,290

*Significant at the 0.10 confidence level.

**Significant at the 0.05 confidence level.

Note: Numbers in parentheses are standard errors. Regressions also include dummy variables that control for missing values.

Source: Authors' computations based on data from the 1997 survey by the Latin-American Laboratory of Quality of Education, as described in the text; UNESCO (2002).

children who have access to more books in the home are less likely to work outside the home. School quality also affects the incidence of child labor. Schools with inadequate supplies encourage child labor. Children in schools with more non-Spanish or non-Portuguese language speakers among their peers are also more likely to work outside the home. Schools that offer more classes in Spanish or Portuguese and mathematics per week also lower the incidence of child labor. In general, these results suggest that better schooling inputs in the home and school lower the incidence of child labor. The exception is that attending preschool does not have a significant effect on child labor in this sample.

The joint test of the null hypothesis that the instrumental variables have no effect on child labor is easily rejected. Variation in truancy laws across countries and in the child labor market for boys within countries does shift the probability that children work. The impact of these laws on the average incidence of child labor is illustrated in figures 1 and 2. The effect was disabled below age 10. As the school starting age rises from ages 5 to 7, the probability of child labor rises about 6 percentage points for a 10-year-old, all else equal, and by 10 percentage points for a 14-year-old (figure 1). As the school-leaving age rises from 12 to 16 years old, the probability of child labor falls by 8.5 percentage points for a 10-year-old and by 11.5 percentage points for a 14-year-old (figure 2). These results suggest that truancy laws do have an effect on child labor on average.

Regional variation in the market for child labor shifts child labor supply for boys and girls (figure 3). The dummy variable spline effectively fixes child labor intensity for children under 10 years of age. After the age of 10, child labor intensity rises for both boys and girls. In each market, boys work more than girls.[16] The higher market labor force participation for boys is consistent with the presumption that the marginal product of child labor is higher for boys than girls. However, rural girls have higher labor force participation than metropolitan boys.

VI. Child Labor and School Achievement

The results from estimating equation (2) both with and without controls for the endogeneity of child labor are reported in table 3. In the specification in table 3, when child labor is treated as exogenous, it takes the values of 0 (almost never work), 1 (sometimes work), or 2 (often work). When treated as endogenous, child labor is a continuous variable with domain over the real line taken as the fitted values from the ordered probit estimation in table 2. The rest of the regressors are the child, household, parent, and school variables used as regressors in table 2.[17]

16. Ages are truncated below 8 (0.4 percent of the sample) and above 15 (0.8 percent of the sample) because of insufficient observations to generate reliable child labor supply trajectories.

17. Similar estimates of the adverse effect of child labor on test scores were obtained when a school-specific fixed effect was used to control for the impact of variation in school and community variables instead of the vector of school and community variables.

TABLE 3. Least Squares and Instrumental Variables Equations on Test Scores

	Child Labor Exogenous[a]		Child Labor Endogenous[b]	
Variable	Mathematics Test Scores	Language Test Scores	Mathematics Test Scores	Language Test Scores
Work outside	−1.184 (0.051)**	−1.087 (0.036)**	−7.603 (1.248)**	−3.980 (0.484)**
Beta coefficient[c]	[–0.159]	[–0.204]	[–0.408]	[–0.295]
Child				
Age	0.097 (0.027)**	0.045 (0.019)**	0.309 (0.070)**	0.162 (0.024)**
Boy	0.731 (0.079)**	−0.165 (0.056)**	2.480 (0.358)**	0.679 (0.155)**
No preschool	−0.256 (0.093)**	−0.181 (0.066)**	−0.376 (0.088)**	−0.079 (0.040)**
Parents/household				
Parent education	0.327 (0.036)**	0.280 (0.026)**	−0.107 (0.106)	0.134 (0.042)**
Books at home	0.735 (0.061)**	0.497 (0.042)**	0.196 (0.100)**	0.258 (0.037)**
School				
Spanish enrollment/100	−0.046 (0.008)**	0.022 (0.006)**	−0.079 (0.010)**	0.007 (0.005)
Inadequate supply	−0.329 (0.046)**	−0.357 (0.031)**	0.073 (0.096)	−0.140 (0.038)**
Math/week (Spanish/week)	0.027 (0.017)	0.022 (0.006)**	−0.073 (0.016)**	−0.049 (0.012)**
Community				
Urban	0.730 (0.107)**	0.240 (0.076)**	1.847 (0.225)**	0.794 (0.117)**
Rural	−0.692 (0.122)**	−0.893 (0.087)**	1.641 (0.410)**	0.275 (0.202)
Constant	13.778 (0.446)**	10.657 (0.248)**	14.400 (0.453)**	8.045 (0.391)**
R^2	0.084	0.127	0.063	0.091
Number of observations	20,699	20,290	20,699	20,290

*Significant at the 0.10 confidence level.

**Significant at the 0.05 confidence level.

Note: Regressions also include dummy variables controlling for missing values.

[a]Numbers in parentheses are standard errors.

[b]Numbers in parentheses are bootstrap standard errors.

[c]The beta coefficients indicate the number of standard deviations the test score will change from a 1 standard deviation increase in child labor.

Source: Authors' computations based on data from the 1997 survey by the Latin-American Laboratory of Quality of Education, as described in the text; UNESCO (2002).

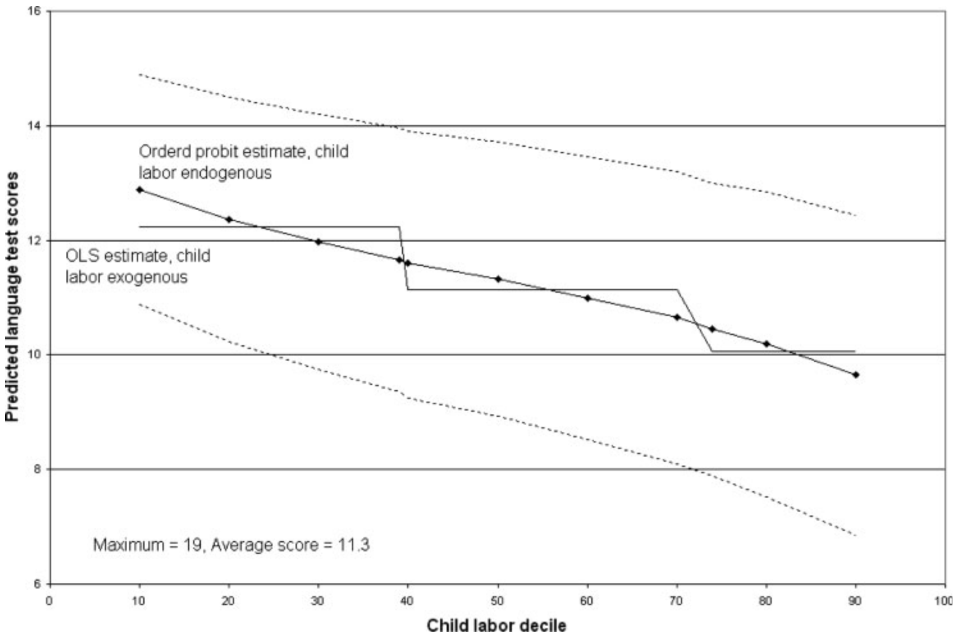
The impact of child labor on test scores is negative and significant whether child labor is treated as exogenous or endogenous.[18] Because of the difference in the scale of measured child labor across the two specifications, it is difficult to directly compare the magnitude of the implied effect of child labor on test scores. The results are compared in two ways. First, the implied effect of a 1 standard deviation increase above the mean in child labor is computed in each of the equations. When treated as exogenous, a 1 standard deviation increase in child labor causes both mathematics and language tests scores to fall by about 0.2 standard deviations. In other words, children working 1 standard deviation above the mean score on average 8 percent lower on mathematics examinations and 6 percent lower on language examinations than do otherwise identical children working at the mean level. When controlling for endogeneity, the effect increases to 0.4 standard deviation (16 percent) drop in the mathematics examination and a 0.3 standard deviation (11 percent) drop in the language examination. This finding that the magnitude of the child labor effect on academic achievement rises after controlling for endogeneity is consistent with results reported by Tyler (2003) and Stinebrickner and Stinebrickner (2003) for older U.S. students.

Second, the two sets of estimates are compared by tracing the predicted mathematics and language test scores at each decile of the reported and predicted child labor distributions (figures 4 and 5). At the breakpoints of the exogenous measure (going from child labor level 0 to level 1 at the 40th percentile and from level 1 to level 2 at the 74th percentile), the predicted test scores using the reported and corrected measures are close to one another. However, the relationship is steeper at the upper and lower tails of the distribution of predicted child labor, particularly for the mathematics test. The implication is that the impact of child labor on test scores is understated in the first two columns of table 3 by restricting the range of child labor to three discrete levels.

Glewwe's (2002) review of the human capital literature in developing countries argued that cognitive ability as measured by test scores is strongly tied to later earnings as an adult. Returns to schooling for those who worked as children would therefore be expected to be lower than for those who did not work, all else equal. Consistent with that expectation, Ilahi, Orazem, and Sedlacek (forthcoming) found that, holding constant years of schooling completed, Brazilian adults who worked as children received 4–11 percent lower returns per year of schooling completed. The estimates here suggest that child labor outside the home reduces achievement per year of schooling attended by 11–16 percent. Because many of the third and fourth graders in the sample will repeat the grade, the estimates are an upper-bound measure of the lost human capital per year

18. The Davidson–MacKinnon (1993, pp. 237–40) variant of the Hausman test easily rejected the assumption of exogeneity of child labor. The overidentification tests of the instruments failed to reject the null hypothesis of exogeneity at the 10th percentile in the language test sample and at the 5th percentile for the mathematics test sample.

FIGURE 4. Predicted Language Test Scores by Child Labor Decile



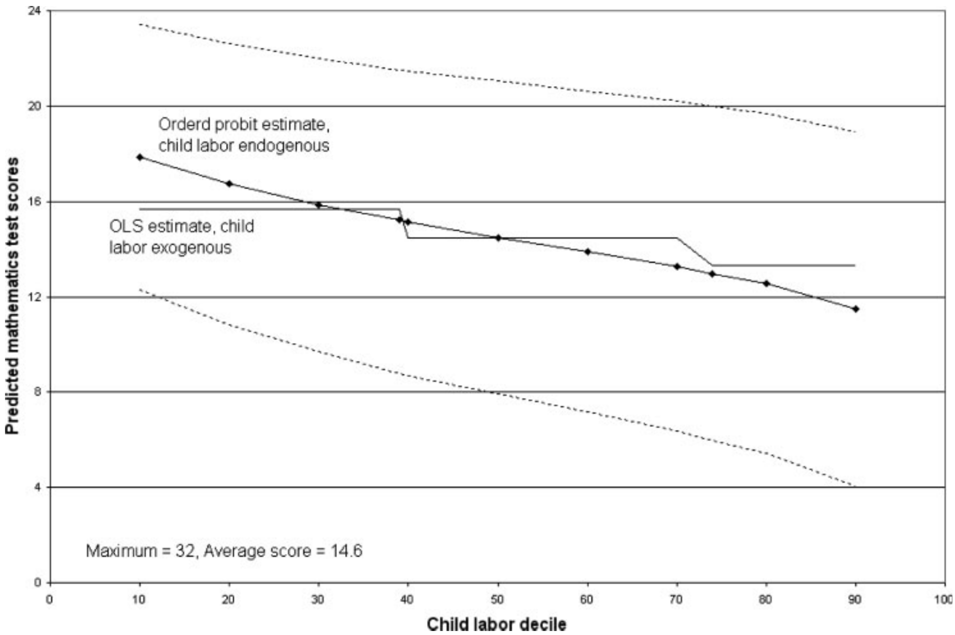
Note: Dashed lines shows 1 standard deviation confidence band for ordered probit estimates.
Source: Authors' simulations based on results in table 3, column 4.

completed, and so the results correspond closely in magnitude to the estimates of Ilahi, Orazem, and Sedlacek of adverse impacts of child labor on earnings.

Most of the other variables have similar effects across the two sets of estimates in table 3, with two main exceptions. The adverse effects of being a boy or being in a rural school disappear in the instrumented equations. Gender and rural residence are closely tied to the incidence of child labor. It is likely that the negative effects on test scores of being male and being in a rural area are related to the indirect effect of these variables on the higher probability that male and rural children work.

Parental education and availability of books in the home lose influence on test scores after controlling for the endogeneity in child labor. School attributes also become less important in explaining test scores. Again, these factors had strong negative effects on child labor, and so part of their positive effect on school outcomes presumably works through their impact on child school attendance and reduced time at work. The literature on the extent to which school quality can explain variation in school achievement has emphasized the large variation in coefficients for the same school inputs across studies and country settings (Hanushek and Luque 2003). The results here suggest that one reason for the uncertain impact of school attributes may be that school quality is more important in affecting school attendance and child labor than in directly affecting test scores.

FIGURE 5. Predicted Mathematics Test Scores by Child Labor Decile



Note: Dashed lines shows 1 standard deviation confidence band for ordered probit estimates.
Source: Authors' simulations based on results in table 3, column 3.

VII. CONCLUSIONS

Working outside the home lowers average school achievement in samples of third and fourth graders in each of the nine Latin-American countries studied. Child labor is shown to have significant adverse effects on mathematics and language test scores using various specifications correcting for possible endogeneity and measurement error in self-reported child labor intensity. Children who work even occasionally score an average of 7 percent lower on language examinations and 7.5 percent lower on mathematics examinations. There is some evidence that working more intensely lowers achievement more, but these results are more speculative in that empirical models were unable to distinguish clearly between working "sometimes" and working "often."

These adverse effects of child labor on cognitive ability are consistent in magnitude with the estimated adverse effects of child labor on earnings as an adult. Thus, it is plausible that child labor serves as a mechanism for the intergenerational transmission of poverty, consistent with empirical evidence presented by Emerson and Souza (2003) and the theoretical models of poverty traps advanced by Basu (2000), Basu and Van (1998), and Baland and Robinson (2000).

Such large effects suggest that efforts to combat child labor may have substantial payoffs in the form of increased future earnings or lower poverty rates once children become adults. How to combat child labor is less clear. The child labor supply equations developed here suggest that truancy laws have some effect in lowering the incidence of child labor. However, most of the variation in child labor occurs within countries and not across countries, so policies must address local child labor market and poverty conditions as well as national circumstances in combating child labor. Policies that alter the attractiveness of child labor or bolster household income, such as income transfer programs that condition receipt on child enrollment or reduced child labor, are likely candidates. Recent experience with such programs in Brazil, Honduras, Mexico, and Nicaragua appears to support further development and expansion of such programs.

Appendix

Table A-1. Variable Description

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)
Often	Student reports that he or she often works outside the home (C)
Sometimes	Student reports that he or she sometimes works outside the home (C)
Almost never	Student reports that he or she almost never works outside the home (C)
Exogenous variables	
Child	
Age	Student age (years) (C)
d10	Dummy variable if student is below 10 years old
Boy	Dummy variable if student is a boy (C)
No preschool	Student did not attend preschool/kindergarten (C)
Parents/household	
Parent education	Average education of parent(s) or guardian(s) (P)
Books at home	Number of books in student's home (P)
School	
Spanish enrollment	Total number of Spanish (Portuguese) speaking students enrolled (Pr)
Inadequate supply	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 1 million people or more)	
Urban	Dummy variable indicating if school is located in an urban area (2,500 to 1 million people) (S)
Rural	Dummy variable indicating if school is located in a rural area (fewer than 2,500 people) (S)
Instruments	
Legal structure	
Compulsory start	Compulsory school starting age in the country (U)
Compulsory end	Compulsory school ending age in the country (U)

Note: C, child survey or test; P, parent's survey; T, teacher's survey; Pr, principal's survey; S, survey designer's observation of socioeconomic characteristics of school community; UNESCO estimate.

Source: Authors' analysis based on data from the 1997 survey by the Latin-American Laboratory of Quality of Education, as described in the text; UNESCO (2002).

TABLE A-2. Summary Statistics

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Endogenous variables					
Mathematics score	20,699	14.62	5.87	0	32
Language score	20,290	11.30	4.22	0	19
Work outside	20,699	0.86	0.79	0	2
Often	20,699	0.25	0.43	0	1
Sometimes	20,699	0.36	0.48	0	1
Almost never	20,699	0.39	0.49	0	1
Exogenous variables					
Child					
Age	20,699	9.95	1.59	6	18
d10	20,699	0.46	0.50	0	1
Boy	20,699	0.50	0.50	0	1
No preschool	20,699	0.25	0.43	0	1
Parents/household					
Parent education	20,699	1.66	1.62	0	6
Books at home	20,699	1.61	1.22	0	4
School					
Spanish enrollment	20,699	439.51	548.82	0	452
Inadequate supply	20,699	3.68	2.73	0	7.93
Math/week	20,699	4.66	3.35	0	30
Community					
Urban	20,699	0.45	0.50	0	1
Rural	20,699	0.35	0.48	0	1
Instruments					
Compulsory start	20,699	5.94	0.74	5	7
Compulsory end	20,699	13.74	1.13	12	16

Source: Authors' computations based on data from the 1997 survey by the Latin-American Laboratory of Quality of Education, as described in the text; UNESCO (2002).

REFERENCES

Akabayashi, Hideo, and George Psacharopoulos. 1999. "The Trade-Off Between Child Labor and Human Capital Formation: A Tanzanian Case Study." *The Journal of Development Studies* 35(5): 120–40.

Angrist, Joshua D., and Alan B. Krueger. 1991. "Does Compulsory School Attendance Affect Schooling and Earnings?" *The Quarterly Journal of Economics* 106(4): 979–1014.

Baland, Jean-Marie, and James A. Robinson. 2000. "Is Child Labor Inefficient?" *The Journal of Political Economy* 108(4): 663–79.

Basu, Kaushik. 2000. *Analytical Development Economics: The Less Developed Economy Revisited.* Cambridge, MA: MIT Press.

Basu, Kaushik, and Pham Honang Van. 1998. "The Economics of Child Labor." *The American Economic Review* 88(3): 412–27.

Basu, Kaushik, and Zafiris Tzannatos. 2003. "The Global Child Labor Problem: What Do We Know and What Can We Do?" *The World Bank Economic Review* 17(2): 147–73.

Ben Porath, Yoram. 1967. "The Production of Human Capital and the Lifecycle of Earnings." *The Journal of Political Economy* 75(4): 352–65.

Card, David. 1999. "The Causal Effect of Education on Earnings." In Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, vol. 3A. Amsterdam: Elsevier.

D'Amico, Ronald. 1984. "Does Employment During High School Impair Academic Progress?" *Sociology of Education* 57(3): 152–64.

Davidson, Russell, and James G. MacKinnon. 1993. *Estimation and Inference in Econometrics*. Oxford: Oxford University Press.

Edmonds, Eric V., and Nina Pavcnik. 2005. "Child Labor in the Global Economy." *The Journal of Economic Perspectives* 19(1): 199–220.

Ehrenberg, Ronald G., and Daniel R. Sherman. 1987. "Employment While in College, Academic Achievement, and Postcollege Outcomes." *The Journal of Human Resources* 22(1): 1–23.

Emerson, Patrick M., and André Portela Souza. 2003. "Is There a Child Labor Trap? Inter-Generational Persistence of Child Labor in Brazil." *Economic Development and Cultural Change* 51(2): 375–98.

Glewwe, Paul. 1996. "The Relevance of Standard Estimates of Rates of Return to Schooling for Educational Policy: A Critical Assessment." *Journal of Development Economics* 51(2): 267–90.

———. 2002. "Schools and Skills in Developing Countries: Educational Policies and Socioeconomic Outcomes." *Journal of Economic Literature* 40(2): 436–82.

Hanushek, Eric A. 1995. "Interpreting Recent Research on Schooling in Developing Countries." *The World Bank Research Observer* 10(2): 227–46.

Hanushek, Eric A., and Javier A. Luque. 2003. "Efficiency and Equity in Schools Around the World." *Economics of Education Review* 22(5): 481–502.

Heady, Christopher. 2003. "What is the Effect of Child Labour on Learning Achievement? Evidence from Ghana." *World Development* 31(2): 385–98.

Heckman, James J. 1976. "A Life-Cycle Model of Earnings, Learning, and Consumption." *Journal of Political Economy* 84(4): S11–44.

Howard, Ian. 1998. "Does Part-Time Employment Affect A-Level Grades Achieved?" PSSI Forum N26 (October): 10–11.

Huffman, Wallace E., and Peter F. Orazem. 2006. "Agriculture and Human Capital in Economic Growth: Farmers, Schooling, and Nutrition." In R. E. Evenson, P. Pingali, and T. P. Schultz, eds., *Handbook of Agricultural Economics*, vol. 3. Amsterdam: North Holland.

Ilahi, Nadeem, Peter F. Orazem, and Guilherme Sedlacek. Forthcoming. "Child Labor, Schooling, and Poverty in Latin America." In Peter F. Orazem, Guilherme Sedlacek, and P. Zafiris Tzannatos, eds., *Child Labor and Education in Latin America*. Washington, D.C.: InterAmerican Development Bank.

Kremer, Michael R. 1995. "Research on Schooling: What We Know and What We Don't; A Comment on Hanushek." *The World Bank Research Observer* 10(2): 247–54.

Levy, Victor. 1985. "Cropping Pattern, Mechanization, Child Labor, and Fertility Behavior in a Farming Economy: Rural Egypt." *Economic Development and Cultural Change* 33(4): 777–91.

Lillydahl, Jane H. 1990. "Academic Achievement and Part-Time Employment of High School Students." *Journal of Economic Education* 21(3): 307–16.

Moll, Peter. 1998. "Primary Schooling, Cognitive Skills and Wages in South Africa." *Economica* 65(258): 263–84.

Patrinos, Harry A., and George Psacharopoulos. 1997. "Family Size, Schooling, and Child Labor in Peru—An Empirical Analysis." *Journal of Population Economics* 10(4): 387–405.

Post, David, and Suet-ling Pong. 2000. "Employment During Middle School: The Effects on Academic Achievement in the U.S. and Abroad." *Educational Evaluation and Policy Analysis* 22(3): 273–98.

Psacharopoulos, George. 1997. “Child Labor versus Educational Attainment: Some Evidence from Latin America.” *Journal of Population Economics* 10(4): 337–86.

Ray, Ranjan. 2000. “Child Labor, Child Schooling, and Their Interaction with Adult Labor: Empirical Evidence for Peru and Pakistan.” *The World Bank Economic Review* 14(2): 347–67.

Ravallion, Martin, and Quentin Wodon. 2000. “Does Child Labor Displace Schooling? Evidence on Behavioral Responses to an Enrollment Subsidy.” *The Economic Journal* 110(462): C158–75.

Rosati, Furio Camillo, and Mariacristina Rossi. 2003. “Children’s Working Hours and School Enrollment: Evidence from Pakistan and Nicaragua.” *The World Bank Economic Review* 17(2): 283–95.

Rosenzweig, Mark R. 1980. “Neoclassical Theory and the Optimizing Peasant: An Econometric Analysis of Market Family Labor Supply in a Developing Country.” *The Quarterly Journal of Economics* 94(1): 31–55.

Rosenzweig, Mark R., and Robert Evenson. 1977. “Fertility, Schooling and the Economic Contribution of Children in Rural India: An Econometric Analysis.” *Econometrica* 45(5): 1065–79.

Sedlacek, Guilherme, Susanne Duryea, Nadeem Ilahi, and Masaru Sasaki. Forthcoming. “Child Labor, Schooling, and Poverty in Latin America.” In Peter F. Orazem, Guilherme Sedlacek, and P. Zafiris Tzannatos, eds., *Child Labor and Education in Latin America*. Washington, D.C.: InterAmerican Development Bank.

Singh, Kusum. 1998. “Part-Time Employment in High School and Its Effect on Academic Achievement.” *The Journal of Educational Research* 91(3): 131–39.

Singh, Kusum, and Mehmet Ozturk. 2000. “Effect of Part-Time Work on High School Mathematics and Science Course Taking.” *The Journal of Educational Research* 91(2): 67–74.

Stern, David. 1997. “Learning and Earning: The Value of Working for Urban Students.” *ERIC Digest* 128. New York: ERIC Clearinghouse on Urban Education, Teachers College, Columbia University.

Stinebrickner, Ralph, and Todd R. Stinebrickner. 2003. “Working During School and Academic Performance.” *Journal of Labor Economics* 21(2): 449–72.

Tyler, John H. 2003. “Using State Child Labor Laws to Identify the Effect of School-to-Work on High School Achievement.” *Journal of Labor Economics* 21(4): 381–408.

UNESCO (United Nations Educational, Scientific, and Cultural Organization). 2002. *Education Statistics 2001—Regional Report on Latin America*. Paris. (http://portal.unesco.org/uis).