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This paper reviews the issues surrounding the derivation of estimates of the impact of child labor on school outcomes. The paper aims to review the current state of methodological and empirical knowledge concerning the impact of child labor on learning, to review existing data sets that could be used to address the issues, and to highlight areas where current research is lacking.

The discussion begins with a conceptual model of the interrelationship between child participation in school and in the labor force that highlights the various factors that enter these decisions. The discussion proceeds to a review of methods to estimate the impact of child labor on student learning using educational production functions. The fact that child labor and school attendance are influenced in part by the child's performance in school complicates the estimation of the impact of child labor on learning.

Armed with this conceptual framework, we turn to alternative measures of the conceptual variables. The pros and cons of various measures of child labor and school performance are presented along with references to how these measures have been used in practice. The need for measures of school and household attributes as well as possible instruments that could be used to control for the endogeneity of child labor are also reviewed.

Next, the paper reviews issues regarding how one might design a sample survey to measure the consequences of child labor for school outcomes. The properties of existing data sets that have been used to analyze these questions are presented. The methodological issues reviewed in the first three sections of the paper are then illustrated using two multinational data sets, one from Latin America and one concentrated primarily on Central and Eastern Europe. Findings from previously published studies of the impact of child labor on schooling outcomes are reviewed. The paper concludes with a summary of questions that have not been adequately settled by existing research and data sets and makes suggestions for future research.

I. Theory of Child Labor and School Attendance

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

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

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

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

decreases as years of schooling rises.[2] These assumptions are sufficient to predict that a child will decrease time in school as the child ages.[3]

The first stage is defined as the length of time the child spends full time in school, so attendance, $A = 1$. In the second stage, $0 < A < 1$, meaning the child divides time between school and work. In the third stage, the child specializes in working, setting $A = 0$. The length of stage 1 or stage 2 varies with the parents' assessment of the value of current child labor versus the present value of increased human capital from spending time in school.[4]

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

The child will attend school if

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

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

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

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

or

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

Condition (1) says the child should attend if the present value of the wage increase attributable to schooling exceeds the cost of child time in school. If condition (1) holds with inequality, A will be set equal to 1 and the child will spend the period in stage 1. If the condition holds with equality, optimal attendance will be in stage 2 where $0 < A < 1$. If the condition is violated, then the child will be in stage 3 where $A = 0$.

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

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

i) Child labor market: the strength of the market for child labor can be measured by the local market wage for children, $W(H_0)$. Child wages would be expected to vary by age, by sex, and by the rural nature of the community. If information on child wages is not available, one can use information on age, sex and rural nature of the community as good proxies. Higher order combinations of these variables may serve as suitable instruments for child labor in the absence of good wage information. An increase in the child wage rate without a corresponding increase in anticipated future wages would shift the attendance schedule to the left as in Figure 2.[5] Children would move into stages 2 and 3 at younger ages.

ii) Past accumulations of human capital: Current human capital accumulation has an ambiguous effect on attendance stage because it can raise both current wages and school productivity. However, if the child wage is dependent more on a child's physical stature than the child's schooling attainment, higher acquired human capital would shift the attendance schedule in Figure 1 to the right.

Past accumulations of human capital are typically measured by school attainment. However, an important component of past accumulations of human capital is unmeasured ability. More able children will succeed more readily in school, but the unmeasured ability may also have an impact on child labor status. As we will demonstrate formally in the next section, missing information on ability endowments can bias the estimated relationship between child labor and school achievement if, for example, children with smaller ability endowments have lower test scores but are also more likely to work.

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

Partial controls for this missing ability endowment may include the use of IQ tests such as the Ravens score or by the inclusion on information on the parents' human capital. However, the problem of ability bias is unlikely to be convincingly resolved with only cross sectional data. The conclusion from numerous studies of the impact of ability bias on estimated returns to schooling has concluded that the bias is small (Card, 1999). While of some comfort, there is no guarantee that the bias from missing ability on estimates of the impact of child labor on achievement would also be small.

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

iv) Household Nonlabor Income, Farm assets, and credit constraints: Nonlabor income will alter condition (1) for two reasons.[6] First, income may make schooling more productive so that $W(H_1) – W(H_0)$ rises as household income increases.[7] The impact of an adverse income shock is illustrated in Figure 2. If the income loss lowers schooling productivity, the attendance schedule shifts to the left, causing children aged t_0 to t_1 to enter the labor market that would otherwise be full-time in school. The shock would also induce

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

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

children aged t_2 to t_3 to drop out of school that would otherwise attend part time. A large enough income shock could cause children in stage 1 to move all the way to stage 3.

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

Liquidity constraints can be characterized as a circumstance by which interest rates increase as household income falls. If true, then poor households discount returns to schooling more heavily, the left-hand-side of equation (1) becomes more negative, and their children enter stages 2 and 3 at younger ages. Information on loan rates is not easily obtained, but measures of household wealth or collateral, poverty or income may serve as suitable proxies. Preference would be for wealth measures that are less subject to endogenous labor supply decisions.

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

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

II. Theory of Human Capital Production in Schools

Let child i in household j have current cognitive attainment as measured by a test score be designated by H_{ij}. Child labor status is measured by C_{ij}, and the attributes of their parents, their school and their community is summarized by Z_j. The child's educational production function which explains the current level of cognitive attainment can be defined by the function

(2) $$H_{ij} = H(C_{ij}, Z_j, H_{0ij})$$

where H_{0ij} is the child's past accumulation of cognitive achievement, either from prior schooling or from latent unmeasured ability which is not observable by the researcher.

In principle, one could estimate the impact of child labor on schooling outcomes as the coefficient on child labor in a linear regression approximating equation (2) including an appropriate error term. However, it is likely that these estimates would be biased. The problem is that the parents' decision on child labor is based in part on their observation of their child's success in school. Consequently, C will be endogenous. We could solve this problem by finding variables that change C but not H.

Under standard assumptions about the household's budget constraint and utility, the child labor supply function will be of the form

(3) $$C_{ij} = C(W_{ij}, \underline{W}_{ij}, Y_j, Z_j, H_{0ij})$$

where W_{ij} is the market wage that could be earned by the ith child, $\underline{W}_{ij}$ is an index of the wages of other members in the household, Y_j is household nonlabor income, and the other elements are defined above. Market wages can be used as instruments to identify child labor in equation (2).[8]

A compounding problem in estimating (2) is the presence of past human capital accumulations, H_{0ij}. Child labor is a function of H_{0ij}, so direct estimation of (2) will be biased due to correlation between the error term that includes H_{0ij} and C_{ij}. Even if C_{ij} is identified by instruments, estimation of (2) may be biased by correlation between H_{0ij} and Z_j. This has led to the use of so-called "value added" specifications where past test scores are used as proxies for H_{0ij}. In those studies, the dependent variable is measured by $H_{ij} - H_{0ij}$, so only the gain in human capital in the current schooling period is used as the dependent variable.

[8] Similar strategies using prices (or time costs implied by distance) as instruments have been employed to identify nutritional demand (Strauss, 1986; Alderman et al, 2001a; Chen et al, 2002); use of prenatal care (Rosenzweig and Schultz, 1983); schooling demand (Gertler and Glewwe, 1990; Alderman et al, 2001b); and the use of health clinics (Alderman and Lavy, 1996).

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

In a single cross sectional data set, the absence of a test score in the base period may be finessed somewhat. First, if the children are all in the same grade, the children must have established at least a threshold level of human capital that qualified the child to be promoted from the past grade level. Second, if the children are at relatively early stages of their schooling, variation across children in H_{0ij} may be small simply because they have not learned much yet. Third, inclusion of other variables that may be viewed as highly correlated with H_{0ij} such as parental education, sibling attributes, Raven's scores or other IQ measures, or other variables which are believed to reflect human capital endowments may be sufficient to control for the missing measure of H_{0ij}. Fourth, if the regressors in (2) change slowly over time, so that school, parent, community, home and child labor measures are nearly unchanged from one year to the next, one can reinterpret equation (2) as representing a cumulative human capital production process including all inputs into the process over the child's school career. This is more likely to be true at early grades. Finally, it should be noted that the two test scores both measure actual cognitive ability with error, so taking the difference between the two may result in a high ratio of noise to the actual change in cognitive ability. If true, than the results from the value added approach may be swamped by measurement error. Nevertheless, it would be better to have the option of testing and rejecting the value added specification than to have no choice except estimating (2) without a measure of H_{0ij} [9]

The general empirical strategy suggested by this discussion is to collect variables that shift the probability of child labor in equation (3) but do not enter the educational production function (2). In designing a new sample, effort should also be taken to establish a measure of H_{0ij} if at all possible.

III. Variable Definitions

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

A. Child Labor

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

GENDER: Another reason to monitor work in the home as well as work outside the home is that girls are more likely to work inside the home while boys are more likely to work outside

[9] Glewwe(2002) has an excellent discussion of these issues.

the home. Concentrating solely on work outside the home may understate the amount of time girls devote to work. Absent strong evidence of the relative adverse consequences of one type of work relative to the other, information on both should be collected.

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

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

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

HAZARDOUS CHILD LABOR: Child labor may also have differential consequences by the type of work conducted. The International Labour Organization's Convention No. 182 advocates the prohibition and elimination of the worst forms of child labor, where the worst forms include the types of child labor that harm child health, safety and moral development.[10] Graitcer and Lerer (1998) provide a comprehensive international review of the state of knowledge of the impact of child labor on health. Data on the extent of child labor itself is subject to considerable error, but data on the incidence of child injuries on the job are even more problematic. Sources of information come from government surveillance, sometimes supplemented by data from worker's compensation or occupational health and safety incidence reports. These latter sources are less likely to be present in the informal labor markets in which child labor is most common, and government surveillance is often weak. Consequently, Graitcer and Lerer conclude that published epidemiological studies of the health consequences of child labor almost certainly underestimate the incidence of injuries. Nevertheless, the rates are not small. Of working children aged 10-14, 9% are estimated to suffer injuries annually, and 3.4% are estimated to suffer disabling injuries. Information on longer term health consequences of child labor such as occupational disease or repetitive injuries is even more limited and subject to errors.

Because the incidence of serious injuries is small in any given year, information on injuries needs to be collected on a large number of working children to get accurate rates. If the interest is in establishing injury rates by occupation, the sample needs to be even larger to get accurate rates by occupation. It is preferable to collect this information from household surveys rather than from formal sector data sources (worker's compensation, mandatory employer

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

disclosure) because most child labor is in the informal sector. Furthermore, we really do not have a good information base on actual risky occupations, so limiting the analysis to specific occupations may miss some dangerous jobs. One way to finesse the sample size problem is to ask retrospective information on injuries over several years. While the retrospective information may be subject to error, it is likely that respondents will remember serious injuries.

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

B. Time in School

ENROLLMENT AND ATTENDANCE: Most of the studies that evaluate the impact of child labor on time in school concentrate on whether or not the child is enrolled. In many countries, enrollment rates for working children do not differ dramatically from those of children who are not working, particularly at younger ages. Some have pointed to this evidence as suggesting that child labor and schooling are not mutually exclusive (Ravallion and Wodon, 2000). Less is known about the relationship between child labor and school attendance because it is more difficult to elicit information on school attendance from household surveys. Parents' impressions of their child's attendance record are likely fraught with error. It is possible to integrate official attendance records from the school with household survey data, but this has not been done frequently in practice.[11]

In the end, time spent in school is an input into the educational production process and is no more a measure of schooling outcomes than is child labor. Both are time allocations. If child labor and time in school are both measured in hours, the time budget imposes an almost certain negative relationship between the two, even if child labor does not harm learning. Consequently, the impact of child labor on learning is unlikely to be well-measured by the impact of child labor on time in school.

LENGTH OF SCHOOL DAY AND TERM: Longer school days may influence the amount a child can learn. However, longer school days also may influence child labor. The longer the school session, the less time a child has to work. Yap et al (2003) found that the imposition of an after school program in rural Brazil resulted in a large reduction in the probability of child labor. Length of term also can affect the amount a child learns in a school year. Differences in the length of school term between black and white schools in the United States in the segregated era have been shown to explain differences in school achievement (Orazem, 1986) and earnings (Card and Krueger, 1992) between blacks and whites.

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

<u>C. School Outcomes</u>

As discussed above, time spent in school is a poor measure of learning in school. Above, we indicated that child labor and time in school may be inversely related, even if child labor does

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

not harm learning. It is also possible that child labor harms learning even if it does not alter time in school. For example, it is possible that child labor does not alter school enrollment, or even that it does not alter school attendance because child leisure is lowered to make time for child work. However, child labor could still adversely affect school outcomes by limiting time spent on homework, or it could leave the child too tired to make efficient use of the time in school. Numerous studies of earnings tell us that it is cognitive achievement or highest grade attained that matter for earnings, not time spent in school per se.

HIGHEST GRADE ATTAINED: Years of schooling completed is a commonly used measure in studies of earnings. It is best used as a measure when the target sample is older and beyond schooling age. Therefore, it is the appropriate measure of schooling for parents and adults. A further complication is that in school-based samples, all children may be in the same grade, so there is no variation in the data.

GRADE-FOR-AGE: When the target sample is younger and still in school, a more appropriate measure is schooling attainment relative to the child's age. This also allows for variation in measures of schooling success even within samples based on the same grade as the most successful students are those who attained the given grade at the youngest age. Researchers must interpret this outcome measure as a multi-year process rather than a single year process, as current grade attainment reflects past as well as current child labor and schooling decisions.

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

DROPOUT AND CONTINUATION: If one is following a cohort of students over time, one can also distinguish dropouts from students who continue on in school. Dropouts reflect both the child's performance and the parents' schooling demand response to the child's performance in school. Consequently, dropouts are less informative about actual success in school than are promotions. Nevertheless, as the model on section 1 demonstrates, the choice to continue in school is related to the child labor market, school quality and past accumulations of human capital and can be analyzed in its own as an element of schooling choices.[12]

TEST SCORES: In the end, it is cognitive achievement and not time in school that policy-makers are targeting. The public or private return to investment in school does not occur the child learns nothing while spending time in the school. In fact, in the few studies that have included both measures, it is measures of cognitive achievement and not years of schooling that are important in explaining variation in adult earnings (Glewwe, 2002). Therefore, if we are to measure the adverse consequences of child labor on a child's human capital development, we must use some measure of cognitive attainment.

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

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

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

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

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

D. Instruments

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

CHILD WAGES AND AGES: The discussion in section 1 indicates that measures of the opportunity cost of child time in school are good instruments for child labor. Child wage is self-explanatory, except that we would need the prevailing child wage by age for boys and girls in each school cluster. If wage is not available, child age is a good substitute as wage and age should be closely related. However, child age is likely related to test scores, making it an invalid instrument. Older children in a given grade are likely to have been held back in the past. However, if the normal age of starting school varies across schools,[13] across different parts of a country, or across countries in multi-country samples, then one can differentiate child time in school from child's age using normal starting school age as a source of exogenous variation in the relationship between age and grade attained. Another alternative is if the age at which children can initially find work in the local labor market varies across school clusters. Note that if local child wage is available, it would be the preferable instrument.

LEGAL VARIATION: Differences in truancy laws, school starting ages, and preschool programs across countries can be used as instruments for child labor across countries. In addition, differences in ability to enforce laws, adhere to demographic principles, or other measures of government capacity of the sort discussed in Kaufmann et al (2002) may vary the cost of

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

compliance with child labor laws. The usefulness of these instruments is limited by the extent to which child labor varies across countries as opposed to within countries, as will be demonstrated in section V.

RANDOMIZED TRIALS AND NATURAL EXPERIMENTS: If children are randomly assigned into child labor, one could use the difference in test scores across the two groups of children as the effect of child labor on school achievement. To our knowledge, that type of randomized trial has not been conducted and is unlikely to pass a human subjects review. However, several examples in Latin America closely approximate that type of experimental design. In Brazil Honduras, Mexico, and Nicaragua, conditional transfer programs have been introduced which tie the receipt of income transfers from the government to proscribed household behaviors. In all the countries, receipt of the transfer was conditional on the child attending school. While receipt of the subsidy was not conditioned on the child not working, it appears that the incidence of child labor declined in Nicaragua (Maluccio, 2003) and in Mexico (Skoufias and Parker, 2003). In the Brazil Bolsa Escola program (Lavinas et al, 2003), child labor did not decline appreciably, but it declined sharply in the rural Brazil PETI program (Yap et al, 2003). What makes the experimental design in all these countries is that the programs were installed in village clusters so that some villages received the program in the first year of its existence and other observationally equivalent villages received the program in later years. The delayed implementation villages serve as controls for the early implementation villages. In Mexico, there was no appreciable change in test scores as a consequence of the reduction in child labor.[14]

Natural experiments would occur when some event changes child labor that is clearly unanticipated and outside the control of the households. One application is the impact of

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

weather shocks on rural households. In India, rural households experience unanticipated temporary increases or decreases in farm income depending on the timing and quantity of the annual monsoon rains. Jacoby and Skoufias (1997) were able to show that adverse income shocks associated with poor rainfall caused households to increase child time in the labor market. The study did not have information on test scores so that we could determine if the increase in child labor was associated with changes in cognitive achievement. In the past, natural experiments tended to be country-specific and accidental, so it is harder to think of a planned natural experiment that could be exploited to identify child labor, either in a single country or across countries. It should also be noted that reliance on weather or income shocks as identifiers requires the use of longitudinal data on households so that departures from household-specific norms fro weather, agricultural production, or income may be identified.

IV. Sampling Issues

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

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

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

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

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

A. Latin-American Laboratory of Quality of Education (LLECE)

In 1997, the First Comparative International Study on Language, Mathematics and Associated Factors was administered in 12 countries of Latin America. Ten of these countries have sufficient information to analyze the impact of child labor on school outcomes: Argentina, Bolivia, Brazil, Chile, Colombia, the Dominican Republic, Honduras, Mexico, Paraguay and Peru. The Cuba sample had too few responses to the child labor question and the Venezuela sample did not report child ages. To our knowledge, this is the best existing data set combining information on child labor and school outcomes for younger children.[15] The sample includes third and fourth graders, so most children are at aged 9-10 years old.

The sample design was based on community size and school type. A school level cluster design was used. Schools were selected from five lists: public and private schools in metropolitan areas with more than one million population, public and private schools from urban areas with between one million and 2,500 people, and public schools from rural areas with less than 2,500 people.[16] Around 100 schools per country were surveyed, and approximately 40 students per school were randomly drawn (20 students in 3rd and 20 in 4th grade). A total of about 4,000 students per country resulted. No information on children not in school was collected.

[15] The TIMSS data set discussed below has a 3rd grade component also, but the data set is plagued by nonreporting and includes very few developing countries.
[16] There are very few private schools in thinly populated rural areas.

Children were given the test at the school. Self-applied questionnaires were given to the children regarding language, time in school, time spent working at home and outside the home, and demographic data. The children's parents (or legal guardians) and teachers were also given self-administered questionnaires, as were the school principals.[17] In addition, surveyors collected information on the socioeconomic characteristics of the community. The final data set includes many more variables than we could summarize here. The variables that proved most relevant to an analysis of child labor and schooling outcomes are described in Table 1, along with their sources. We also include descriptions of country-level measures that were merged into the data set to measure differences in the legal and social environment shaping child labor across the ten countries. These cross-country differences can provide plausible instruments that exogenously shock child labor without affecting test scores. However, the community variable that would have provided the best identification within countries, that being market wages for boys and girls, was not collected.

B. The Third International Mathematics and Science Study (TIMSS)

The International Study Center at Boston College oversaw the collection of the TIMSS in 1995. A follow-up sample is being prepared. The TIMSS is the largest international study of student achievement ever conducted. During 1994-95, the test was administered at five different grade levels in more than 40 countries worldwide. Our analysis concentrated on the 7th and 8th grade samples from the poorer countries in the sample.[18] The focus on the lower income countries was dictated by our interest in child labor, which is less common at these ages in OECD countries that make up the majority of the 40 countries included in the TIMSS. The

[17] The reason the questionnaires were self-administered was to lower the cost of the survey, insuring that more schools and countries could be included. However, this raises concern that the respondents must be literate, so some parental respondents may have been lost.

[18] As mentioned above, the data on the 3rd grade children was not collected for many of the developing countries and did not prove useful for our work on child labor and school achievement.

countries we use included Colombia, Czech Republic, Hungary, Iran, Latvia, Lithuania, Romania, Russia, Slovak Republic and Thailand.[19] While all of these countries fall in the lower-middle-income class or the lower part of the upper middle-income class classification from the 1998 World Development Report, none are as poor as the lower tail of the Latin American sample.

As with the LLECE, the TIMSS was a stratified sample drawn from lists of schools of different sizes. In each school, a 7th and 8th grade class was selected for the study, and all students in the classroom were tested and interviewed. In the TIMSS, some countries applied a third stage by sampling students within classrooms. Information was also collected from teachers, students and principals through questionnaires. No information was collected from parents. A description of the TIMSS variables that we found particularly suited to studies of child labor and school outcomes is reported in Table 2. As with the LLECE, no information on local; child wages was collected.

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

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

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

of child labor and school enrollment, but it cannot address the impact of child labor on school achievement.

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

D. Living Standards Measurement Surveys (LSMS)

The ICRISAT data set was a precursor of the detailed household surveys designed and implemented by the World Bank in a broad range of countries. The first LSMS was collected in 1985 in the Cote d'Ivoire and Peru. They are characterized by very detailed modules covering labor supply behavior of all household members over age 6 plus information on consumption, health, production, fertility, schooling, and wealth indicators. The household information is supplemented by community information including the location and quality of educational, health, water, transportation and other public services. The survey also collects information on commodity prices. Such data allow very detailed studies of factors affecting child labor and time in school, but have not included measures of school achievement. The questionnaire was administered in the household by trained interviewers.

The LSMS has the advantage that parallel modules are administered in many different countries, allowing cross country comparisons to be drawn. This allows cross-country variation in truancy of child labor laws to serve as potential instruments for child labor. The data are of extremely high quality without missing responses because of the use of face-to-face interviews rather than self-administered questionnaires. This avoids problems related to selection on the basis of the literacy of the respondent. Information on all household members is collected, so potential substitution of one child's time for another can be analyzed. The LSMS data sets are very good sources of information for the study of the determinants of child labor and its impact on school enrollment. However, with the exception of the Ghana study (Heady, 2003) , the LSMS has not incorporated test scores so the analysis cannot be carried forward to studies of school achievement.

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

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

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

F. The Statistical Information and Monitoring Programme on Child Labour (SIMPOC)

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

The School-based Surveys collect information on working children who also attend school. The School-based Surveys get teachers' and administrators' perceptions of the intensity of child labor in the local labor market and on how child laborers perform in school. Qualitative responses include perceived absenteeism rates, promotion rates and other schooling outcomes for students who work relative to those who do not work. The survey also elicits impressions of the school-related factors that may influence the incidence of child work, such as the quality of the school and the children's perception of the relevance of their education.

V. Sample Results from the LLECE and TIMSS samples

In this section, we demonstrate the type of results that can be obtained with the two multi-country data sets that include both measures of child labor and test scores. One of the potential benefits of multi-country data sets is that differences in legal environment can serve as exogenous variables shifting the probability of child labor. Unfortunately, ANOVA analysis suggests that the use of country-specific effects may be a weak source of identification. The reason is that in both the LLECE and TIMSS data sets, less than 5 percent of the variation in child labor is attributable to factors that vary across countries. The rest is due to within country variation. This suggests that a successful study must be able to utilize instruments that vary within country as well as across countries.

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

A. Child Labor Supply Estimates

Although the labor supply estimates are interesting in their own right, they are not our primary concern in this paper. In general, the estimates are consistent with expectations of how school quality, opportunity costs, and parental socioeconomic status would influence child time allocations. Being a boy and living in a rural area increases the likelihood of working in the child labor market. Working outside the home increases with age because both physical and mental ability to do work increase with age. The likelihood of working decreases the higher the education of the parents. Speaking the language of the test at home, small family size, living with both parents and having a large number of books at home lowers the incidence of working in the labor market. Generally, school attributes associated with improved school quality lower the incidence of child labor. The country-level measures also proved significant in explaining variation in child labor across countries.

B. Child Labor and School Achievement

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

Table 3 contains sample statistics for alternative measures of cognitive achievement and child labor. In the Latin American data set, child labor is measured by responses from the child as to whether they never work outside the home, whether they work a little, or whether they work a lot. Cognitive achievement is measured by tests of language and math administered to children in the 3rd and 4th grades. In the TIMSS data set, child labor is measured alternatively by an ordered variable indicating the range of hours of work inside and outside the home, and again by a series of dummy variables indicating the relevant hour range. When treated as endogenous, first stage regressions were estimated using ordered probit and the predicted values are used in the second stage educational production function. Standard errors are estimated using a bootstrapping procedure.

To conserve space, we only report the coefficients on the child labor measure. The educational production function also included indicators of child, household, school and community variables whose coefficients are suppressed. We first report the results from the LLECE study conducted by Sanchez et al (2003). Treating child labor status reported by the child as exogenous, they reported sample means of test scores by country for children who worked outside the home "always", "sometime", and "never". Although there are minor variations, the common finding is that for both mathematics and language tests, children who always work perform less well than those who sometimes work, and those that sometimes work perform less well than those who never work. The differences in the mean performance between those who always work and those who ever work are almost always statistically significant. Averaging across all the countries, 3rd and 4th graders who never work performed 27.5% better on the mathematics test and 18.6% better on the language test than did those who always worked. Those who sometimes worked had a 8.8% and 6.9% advantage over those who always worked on the mathematics and language tests respectively. Even after controlling for all the school, home, and parent attributes (referred to as the conditional estimates in Table 4), the adverse impact of child labor remains large and statistically significant.

Those effects do not control for the likely endogeneity of child labor, however. We compare the results with and without controlling for endogeneity in Table 5. Here, we treat child labor as a continuum progressing from never to always working and average the effect of child labor across the various child labor intensities. The first two columns in Table 5 show the estimated impact of child labor on test scores in the LLECE data set when child labor is treated as exogenous. The effect is negative and significant on both math and language scores. The estimated impacts are modest. A one standard deviation increase in child labor lowers both test scores by just under 0.2 standard deviations, which would correspond to a loss of about 7 percentage points if test scores were normally distributed. This corresponds to the estimated effect of working "sometime" relative to "always" in Table 4. When controlling for endogeneity, the magnitude of the effect becomes much larger. A one standard deviation increase in child labor lowers math scores by 0.4 standard deviations and language scores by 0.5 standard deviations.[20] The implication is that treating child labor at the market as exogenous biases the implied adverse impact of child labor toward zero.

[20] To put these results in perspective note that in the standard normal distribution, 68% of the variation is within 1 standard deviation of the mean. Therefore, a drop of 0.5 standard deviations in test scores is a slide down the

Table 6 shows the same results for the TIMSS, except that the TIMSS includes several alternative measures of child labor both inside and outside the home. As with the LLECE estimation, we suppress the coefficients on child, household, school and community variable to conserve space. The first set of results includes a single ordered measure of time spent working outside the home. When treated as exogenous, a one standard deviation increase in child labor lowers 7th and 8th grade math and science test scores by less than 0.07 standard deviations. Controlling for endogeneity, the estimated adverse impact of a one standard deviation increase in child labor rises to -0.12 standard deviations in the mathematics score and -0.16 standard deviations in the science score.

All these effects are large and statistically significant. Nevertheless, it is important to note that the adverse effects of child labor on the 7th and 8th graders are much smaller than the adverse effects on 3rd and 4th graders reported in the Latin American sample. This implies that child labor is costlier in terms of foregone cognitive development at younger relative to older ages.

We attempted a parallel analysis using the child's self-reported time spent in work in the household. When treated as exogenous, the impact was similar to that estimated for work outside the home. However, we could not identify instruments that explained a significant amount of the variation in labor in the household, and so we do not report results for work in the home.

The second set of results uses a dummy variable to indicate the range of hours worked per day. Using zero hours of work as the reference, we estimate the impact of being in work groups of less than 1 hour per day, 1-2 hours, and 3-5 hours. For work in the home, the reference group

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distribution of 17 percentage points. While the distribution of test scores will not be normal, the correspondence is close enough to suggest that the impact of child labor on achievement is substantial. It is also consistent with the magnitude of the decline in adult wages associated with having worked as a child reported by Ilahi et al (2003).

is less than 1 hour per day versus 1-2 hours per day.[21] The results are reported at the bottom of Table 6. The implied proportional change in the standard deviation in test scores relative to the mean is reported under the coefficient and its standard error. The estimates reflect the change in test scores from a movement from no work to the respective work-hours category, evaluated at sample means.

The results are striking. Treating child labor outside the home as exogenous, any job outside the home lowers test scores, even those involving less than an hour of work per day. However the impact is small, involving a decline of only a few percentage points. The adverse impact gets larger as hours of work rise, but never more than a 3% decline. Work in the home actually raises test scores. The implication is that there is a cost to child labor outside the home but that it is modest.

Controlling for endogeneity, jobs involving under an hour a day outside the home lower science but not math scores and the proportional effects are very small. However, working more than an hour per day outside the home has a much larger adverse impact, lowering math scores by at least 10% and science scores by between 11% and 15%. Working longer hours in the home also lowers test scores by between 1% and 2%.

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

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[21] In the TIMSS data set, no children were predicted to work zero hours per day in the home or more than 2 hours per day in the home, so we shrank the number of options to reflect that outcome.

VI. Previous Empirical Studies

A. Child Labor and Time in School

Most of the studies up to this point have focused on the relationship between child labor and school enrollment. It has been commonly observed that in many countries, the majority of working children are enrolled in school. For example, Ravallion and Wodon (2000) found that increases in enrollment in a sample of girls in Bangladesh were not associated with appreciable decreases in child labor. They conclude that the adverse consequences of child labor on human capital development are likely to be small.

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

While child labor appears to be associated with reductions in school attendance, it still does not follow that child labor lowers the development of marketable skills. Many schools in developing countries are of poor quality so that children may receive better informal or on-the-job training outside school. On the other hand, changes in attendance would understate the adverse effect of child labor on human capital accumulation if a child who attends school despite working is too tired too learn or has no time for homework.

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

B. Child Labor and School Achievement

There is indirect evidence that child labor limits a child's human capital development. Child labor has been linked to greater grade retardation (Sedlacek et al., 2003; Rosati and Rossi, 2001); lower years of attained schooling (Psacharopoulos, 1997); and lower returns to schooling and a greater incidence of poverty as an adult (Ilahi et al, 2003). On the other hand, some studies have found that child labor and schooling may be complementary activities (Patrinos and Psacharopoulos, 1997). A definitive answer on whether child labor lowers cognitive attainment requires direct estimation of the educational production function (2).

The majority of studies attempting to analyze the relationship between child labor and school attainment focus on the U.S. and on working while in high school or college. Lillydahl (1990) reported that working part-time in high school actually raised grade point average (GPA) as long as the student worked less than 13.5 hours per week. Working more than that had no adverse consequences on GPA. Ehrenberg and Sherman (1987) concluded that working while in college had little effect on GPA, although it raised the probability of dropout and lengthened the time to graduate.

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

Some studies have found stronger evidence of adverse consequences of child labor on achievement. Singh (1998) reported that working long hours while in school did hurt standardized test scores and grades, although the effect was quite small. Stern (1997) found that working more than 15 hours per week while in secondary school led to lower grades, less time spent on homework, increased likelihood of dropout and a lower likelihood of entering post-secondary education. Similar findings are reported by Cheng (1995) and StatsCan (1994). Singh and Ozturk (2000) explored the linkage between working hours and reported that an increase in hours of part-time work lowered the number of mathematics and science classes taken which in turn led to lower achievement in mathematics and science. Barone (1993) found that younger students working long hours performed more poorly than did working older students.

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

Sánchez et al. (2003) using information on 3rd and 4th graders in Latin America found that in all 10 countries tested, performance on mathematics and language tests was lower when the child worked outside the home, and the impact became larger when the child reported working many rather than few hours.   Heady (2003), made use of a special Living Standards Measurement Survey in Ghana that included information on test scores. He found that child work had relatively little effect on school attendance but had a substantial effect on learning achievement in reading and mathematics. The effect remained strong even after controlling for the child's innate ability using the Raven's test. Because attendance was unaffected, the adverse consequence of child labor on student learning was attributed to exhaustion or lack of interest in academic performance rather than child time in school.

Neither of the two studies corrects for the likely endogeneity of child labor. As discussed in section 2, the coefficient on child labor will be biased if parents decide whether their child will work in part on how the child is performing in school.

Rosati and Rossi (2001) take into account the endogeneity of child labor in their study of grade retardation in Pakistan and Nicaragua. They found that increasing the probability of working raises the likelihood that the child has fallen behind the correct grade for age. The study suffers from missing information on school attributes, and also from rather arbitrary exclusion restrictions used to identify child labor.

Gunnarsson (2003) extends the Sánchez et al study by correcting for the endogeneity of child labor. She makes use of variation in the starting age of schooling and other variation in legal environment across countries as a means of identification. Unfortunately, most of the variation in child labor is within country and not across countries, so this means of identification is somewhat crude. She found that the estimated impact of child labor on test scores becomes more negative when controls for endogeneity are used. Summary information on her results are contained in Tables 4 and 5.

VII. Gaps in the Research Record

As the review of the literature suggests, there are very few studies of the impact of child labor on cognitive achievement at the primary level. Most studies are still in working paper form, so it is probable that there are other studies of which we are not yet aware. Nevertheless, these are the gaps in our knowledge of the damage caused by child labor based on the literature that we have been able to identify.

1) We do not know if there is a threshold level of hours of work at which damage begins, or if any child labor causes damage. Results from the LLECE and TIMSS and Ghana LSMS data sets strongly suggest that the damage done increases with hours of work, that the damage is larger at younger ages, and that even modest amounts of child labor lower cognitive achievement. However, the data are not fine enough to identify whether any level of child labor will cause a loss of cognitive achievement.

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

3) Only two studies have been able to examine work in the home versus work in the market. Evidence appears to suggest that work in the home is less damaging to school achievement than is market work, but more work is needed.

4) Similarly, we do not know if the damage differs by the type of work children do, or if it is subject to the hours worked alone.

5) We have only a few studies that have examined the long-term economic consequences of child labor, and work on long-term health consequences of child labor is even more limited.

Gaps in the existing methodological approaches to chuild labor and student achievement include:

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

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

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

VIII. Type of complementary data that could supplement household data sets

The type of data required to test the impact of child labor on school achievement is laid out in section III. The critical need for auxiliary data is to collect information that will help identify work inside or outside the home. These are a few suggestions.

1) Collect two test scores, one at the beginning if the school year and one at the end. This will allow estimation of the value added specification.

2) Information on the labor market for children can be obtained by aggregating responses on wages paid to children from household surveys in the same community. Alternatively, one can acquire information on employment opportunities and child wages by interviewing informed members of the community.

3) Any information that could vary the cost of or returns to child labor or schooling across communities would be useful. School quality indicators are the most obvious, but they would be related to both child labor and cognitive achievement. What are needed are factors that vary across communities that affect child labor but are not related to test scores.

4) It is important to know the legal climate surrounding child labor and schooling in the country. At what age does a child enter school, what is the truancy age, how long is the school day, and how long is the school year. It is conceivable that some of this information would vary across communities within a country. However, this information is more useful in data sets that span countries, as changes in the legal environment can serve as instruments generating exogenous variation in the probability of child labor across countries.

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Table 1 – Variable Description in the LLECE Data.

Endogenous variables	
Math Score	Mathematics test score (C)
Language Score	Language test score (C)
Work Outside	Index of how often student works outside the home (0-2) (C)
Exogenous variables	
Child	
Age	Student age (years) (C)
d10	Dummy if student is below 11 years old
Boy	Dummy if student is a boy (C)
No Preschool	Student did not attend preschool/kindergarten (C)
Parents/Household	
Parents' Educ	Average education of parent(s) or guardian(s) (P)
Books at Home	Number of books in student's home (P)
Parents Spanish	Dummy variable indicating if parent's native language is Spanish (Portuguese) (P)
Teacher	
Male	Dummy if teacher is male (T)
Teacher Educ	Aggregated teacher education (T)
School	
Total Enr	Total number of students enrolled at school (Pr)
Spanish Enr	Total number of Spanish (Portuguese) speaking students enrolled (Pr)
Inadequacy	Index of school supply inadequacy (Pr)
Math/week	Number of mathematics classes per week (Pr)
Spanish/week	Number of Spanish (Portuguese) classes per week (Pr)
Community *(Reference:* Metropolitan area with 1M people or more*)*	
Urban	Dummy variable indicating if school is located in an urban area (2,500-1M people) (S)
Rural	Dummy variable indicating if school is located in a rural area (less than 2,500 people) (S)
Instruments	
Legal structure	
Comp Start Age	Compulsory school starting age in the country (U)
Comp End Age	Compulsory school ending age in the country (U)
Preprimary	Dummy variable indicating if the country has a compulsory preprimary school year (U)
Marriage	Percentage of 15-19 year olds married in the country (UN)
Stability	Estimate of political stability 2000/01 (KKL)
Regulation	Estimate of regulatory quality 2000/01 (KKL)
Law	Estimate of rule of law 2000/01 (KKL)

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

Table 2 –Variable Description TIMSS Data.

Endogenous variables	
Math Score	Test score mathematics (C)
Science Score	Test score science (C)
Work Paid	Index of how often student works at a paid job per day (1-5) (C)
Work Home	Index of how often student works in the household per day (1-5) (C)
< 1hr. Paid	Dummy if student works less than 1hr. per day at a paid job (C)
1-2 hrs. Paid	Dummy if student works 1-2 hrs. per day at a paid job (C)
3-5 hrs. Paid	Dummy if student works 3-5 hrs. per day at a paid job (C)
1-2 hrs. Home	Dummy if student works 1-2 hrs. per day in the household (C)
Exogenous variables	
Child	
Age	Student age (years) (C)
d13	Dummy if student is below 14 years old
Boy	Dummy if student is a boy (C)
Test Language	Frequency of which student speaks test language (1-3) (C)
Parents/Household	
Mother's Educ	Education level of mother (1-6) (C)
Father's Educ	Education level of father (1-6) (C)
Both Parents	Student living with none, one or two parents (0-2) (C)
People Home	Number of people living at home (C)
Books at Home	Index of number of books in student's home (1-5) (C)
Teacher	
Teacher Age	Teacher age (years) (T)
Male	Dummy if teacher is male (T)
Teacher Educ	Aggregated teacher education (T)
School	
Total Enr	Total number of students enrolled at school (Pr)
Girls Enr	Percentage of girls enrolled of total (Pr)
Shortage	Index of school supply shortages (Pr)
Class Size	Average class size (Pr)
Community	
Rural	Dummy if school is located in a rural area (Pr)
Instruments	
Legal structure	
Comp Start Age	Compulsory school starting age in the country (U)
Comp End Age	Compulsory school ending age in the country (R)
Marriage	Percentage of 15-19 year olds married in the country (UN)
Stability	Estimate of political stability 2000/01 (KKL)
Regulation	Estimate of regulatory quality 2000/01 (KKL)
Law	Estimate of rule of law 2000/01 (KKL)

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

Table .3 – Summary Statistics of the Endogenous Variables in the LLECE and TIMSS Data Sets.

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
LLECE					
Math Score	43861	15.177	6.191	0	32
Language Score	44000	11.570	4.370	0	19
Work Outside	35222	0.789	0.789	0	2
TIMSS					
Math Score	69790	480.390	95.348	180.870	795.413
Science Score	69790	487.378	94.929	82.440	806.714
Work Paid	60984	1.555	1.137	1	5
Work at Home	65885	2.745	0.894	1	5
< 1hr. Paid	60984	0.079	0.270	0	1
1-2 hrs. Paid	60984	0.066	0.249	0	1
3-5 hrs. Paid	60984	0.039	0.194	0	1
1-2 hrs. Home	65885	0.422	0.494	0	1

Table 4 - Average Language and Mathematics Test Scores, By Country and Level of Child Labor. Source: Sanchez, Orazem and Gunnarsson (2003)

	Language Test (Maximum Score = 19)		Mathematics Test (Maximum Score = 32)	
Country	**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%)
Dominican Rep.				
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

	Language Test (Maximum Score = 19)		Mathematics Test (Maximum Score = 32)	
Country	**Unconditional[a]**	**Conditional[b]**	**Unconditional[a]**	**Conditional[b]**
	(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%)
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 county. [b] Based on coefficients of dummy variables for ”Sometime” and ”Never” from country-specific regressions comparable to the specifications reported in Table Y. The regressions also included all the school, teacher and household factors included in Table Y. [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 0.05(*) or 0.01(**) level of significance. [g] Percentage difference relative to children who always work outside the home when not in school.

Table 5 - Least Squares and Instrumental Variables Equations on Test Scores, Latin America.

	Child Labor Exogenous[a]		Child Labor Endogenous[b]	
Variable	**Mathematics**	**Language**	**Mathematics**	**Language**
1, Work Outside the Home				
Work Outside	-1.254*	-1.032*	-6.961*	-6.818*
	(0.045)	(0.028)	(0.460)	(0.571)
Beta Coefficient[c]	-0.162	-0.189	-0.414	-0.549

[a] Standard errors in parenthesis. [b] Bootstrap standard errors in parenthesis. ***** indicates significance at the 0.05 confidence level. [c] The beta coefficient indicates the number of standard deviations the test score changes in response to a one standard deviation increase in child labor. Regressions also included child, household, teacher, school, and community variables.

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

	Child Labor Exogenous[a]		Child Labor Endogenous[b]	
Variable	**Mathematics**	**Science**	**Mathematics**	**Science**
Specification 1: Ordered Measures of Hours of Work				
Work Paid	-5.781*	-5.023*	-27.335*	-36.332*
	(0.326)	(0.333)	(4.263)	(4.499)
Beta Coefficient[c]	-0.068	-0.059	-0.119	-0.159
Specification 2: Dummy Variables Indicating Hours of Work				
< 1 hr. Paid	-3.756*	-7.350*	6.409*	-5.641*
	(1.344)	(1.373)	(3.118)	(3.010)
Proportion[d]	-0.008	-0.015	0.013	-0.012
1-2 hrs. Paid	-9.013*	-7.789*	-56.434*	-71.249*
	(1.465)	(1.497)	(6.799)	(7.563)
Proportion[d]	-0.019	-0.017	-0.117	-0.146
3-5 hrs. Paid	-14.579*	-11.624*	-48.767*	-55.934*
	(1.905)	(1.946)	(11.618)	(13.792)
Proportion[d]	-0.030	-0.024	-0.102	-0.115
1-2 hrs. Home	2.476*	4.402*	-8.355*	-4.039*
	(0.728)	(0.743)	(1.349)	(1.348)
Proportion[d]	0.005	0.009	-0.017	-0.008

[a] Standard errors in parenthesis. [b] Bootstrap standard errors in parenthesis. ***** indicates significance at the 0.05 confidence level. [c] The beta coefficients in Specification 1 indicate the number of standard deviation the test score will change from a one standard deviation increase in child labor. [d] Proportional change in test scores associated with moving from the reference group to the dummy variable group in Specification 2. Regressions also include child, household, teacher, school, and community variables.

Figure 1: Stages of Investment in School

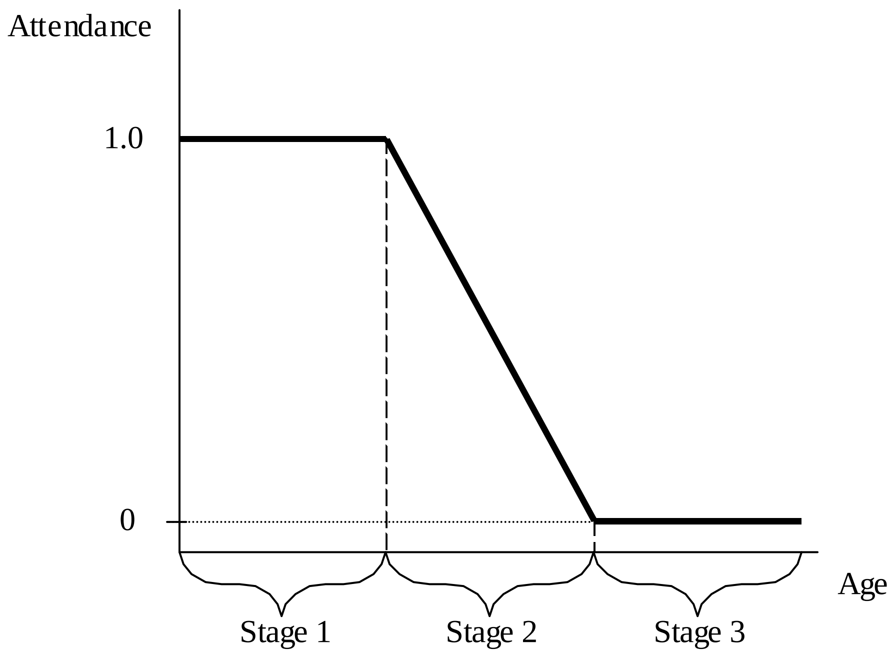

Figure 2: The Impact of Adverse Income Shocks or Child Wage Increases on Investment in School