Why Children Work, Attend School, or Stay Idle: Theory and Evidence

ABSTRACT

This paper offers a theoretical and empirical analysis of child labor, schooling, and 'idleness' (neither work nor school), with particular emphasis on the roles of child ability and credit constraints in determining these decisions. We show theoretically that 'idleness' may be chosen optimally by borrowing-constrained households whose child is of low ability. As well, children in the poorest households combine work and schooling if they are sufficiently able. Using a rich dataset from the Philippines, we find that while other factors–including mother's labor supply, the presence of a family business, and access to good school quality–contribute to these decisions, child ability and household wealth are the most important determinants of child idleness and the use of child labor. Our results suggest that the appropriate policy focus is not a ban on child labor, which may only increase the pool of idle children, in some cases by decreasing child schooling. Any policy aiming to reduce child labor and increase child schooling should also target improvements in child ability and cognitive development through investments in the nutrition and health of poor children.

JEL Codes: I20, J13, J22, O15

1 Introduction

Despite the continued economic progress among developing countries over the last several decades, the phenomenon of child labor still remains widespread. According to a recent ILO report, one in six of the world's children between the ages of 5 and 17 work–and the proportion is higher in the poorer parts of Asia and Africa. Given the moral outrage on the issue of child labor and the increasing willingness of governments and international organizations to enact and fund policy measures to deal with this problem, it is imperative to understand the determinants of child labor in order to make informed policy decisions. In this paper we seek to understand the determinants of child labor and children' activities more generally.

There is a rapidly growing theoretical and empirical literature on child labor following the works of Grootaert and Kanbur (1995) and Basu and Van (1998)[1]. The recent literature has shown how the inability of the child or child's parents to access credit markets can lead to inefficient educational attainment not only within a generation but even across generations (Baland and Robinson 2000, Ranjan 2001, Basu 1999). Child labor can be a "dynastic trap" because a child who acquired less education due to work will grow up to also be poor as an adult. In turn, as a poor adult parent, this person would send his or her children to work[2]. The existing literature, however, has ignored the role of child-specific qualities such as ability and motivation and their potential interaction with household wealth in determining child labor decisions, which is the focus of our paper. We thus begin by developing a model of household decision-making that highlights how liquidity constraints and differences in child endowment jointly determine parents' decisions on childrens' activities. The predictions of our model with borrowing constraints form the basis for our empirical investigation using data from the Philippines.

[1]See Brown et al. (2003) and Basu and Tzannatos (2003) for recent surveys of literature on child labor.
[2]See Emerson and Souza (2003) for the empirical support of intergenerational persistence of child labor.

Our paper offers three main contributions. First, while much of the child labor literature tends to highlight the importance of credit markets, our theoretical and empirical investigation consider the role of child ability in the presence of these liquidity constraints. Our work is therefore relevant among recent studies seeking to establish the empirical link between income shocks, measures of access to credit, and child labor supply (among these are Beegle, Dehejia, and Gatti (2003) and Edmonds (2004))–and adds to this the issue of student ability. More importantly, our results show that, in our sample, it is student ability that is far more important than any other factor in determining child labor and school non-enrollment.

Another contribution of our paper is to distinguish between the roles of child ability, household wealth, and school quality in child labor decisions. There is little empirical research that distinguishes between a child's ability, household wealth, and school quality as determinants of childrens' activities, in part due to lack of data. The survey we employ, the Cebu Longitudinal Health and Nutrition Survey (CLHNS), contains a particularly rich set of information. In addition to information on children's activities, data collected include children's performance on an IQ test (our measure of ability), household expenditures and assets, and characteristics of schools in the area to generate measures of school quality.

Separately accounting for these factors is quite significant in light of the literature. In their review of empirical evidence on the determinants of child labor, Brown et. al. (2003) note that the relationship between family income and child labor supply is not always so clear cut.[3] While there is a strong cross-country negative correlation between child labor and per capita GDP, at the household level this relationship is not as evident. In some studies, household expenditures do not play a significant role in child labor decisions, and family income is not so predominant in explaining variations within a community. They hypothesize

[3] Studies reviewed by Brown et. al. typically estimate reduced-form participation equations for child work, and were from Colombia, Bolivia, Peru, Ghana, Cote d'Ivoire, Zambia, India, and the Philippines. Another survey on child labor by Basu and Tzannatos (2003) note that some early research found that the effect of adult income was often negative but small (at times insignificant) after controlling for other variables.

that (uncaptured) poor school quality may be driving the ambiguity in these results, as bad schools lower the value of education. In controlling directly for measures indicating the availability of school quality and some measure of child-specific heterogeneity, we are able to distinguish between the roles of family income, child ability, and school quality in determining child labor decisions. Assessing the separate roles of these factors may also shed light on important policy implications.

Our third primary contribution is in considering 'idleness' explicitly as one of the activities taking up child's time along with schooling and work. Most of the theoretical and empirical literature on child labor fails to distinguish between alternative non-work activities, implicitly treating schooling as the only alternative to work (e.g., Ravallion and Woodon 2000, survey article by Brown et. al. 2003). Recent studies, such as Rosati and Tzannatos (2002), Deb and Rosati (2002), have begun to note that a considerable fraction of children are actually neither in school nor engaged in outside work. This category is increasingly being referred to as 'idleness'.[4] At first blush it may seem odd that utility maximizing households will choose 'idleness' over work or schooling for their children. We show, however, that in the presence of a disutility from child work and a direct cost of education, 'idleness' may be chosen optimally by borrowing-constrained households whose child is of low ability.

Considering 'idleness' explicitly as a separate activity from child labor and schooling is also significant from a policy perspective. We show that in the presence of borrowing constraints banning child labor may not only increase the pool of idle children by moving some children who were working full time to the 'idle' category; banning child labor could actually reduce the amount of schooling, by sending some of the children who would otherwise both work and attend school to the 'idle' category. Given a positive direct

[4] Using data from the Living Standard Measurement Survey (LSMS) in Vietnam, Rosati and Tzannatos (2002) report that 3% of children in 1993 and 2.2% in 1998 were in the 'idle' category. Deb and Rosati (2002) find, using survey data, that 14% of children from Ghana were 'idle' in 1997, while for India this number was 23% in 1994. In our sample from the Philippines, 'idle' children constitute 4.3 percent.

cost of schooling, some parents may not be able to afford schooling if their children are not allowed to work part-time. Thus, if increasing child schooling is the objective of policy, then failure to take the 'idleness' option into account may result in erroneous policy conclusions.

Such unintended consequences of banning child labor arise whether or not children are really 'idle' or engaged in unpaid home production. Because of the structure of most survey questionnaires child labor often refers to paid outside work; thus, children classified as 'idle' may be actually engaged in unpaid home production. Yet, they may also be idle because outside work opportunities do not exist, while at the same time, parents cannot send them to school because of perceived low return to schooling. Access to schooling may be difficult (due to distance), or even when there is access, parents could perceive a low return to schooling if the surrounding schools are of low quality. A low return to schooling could also be perceived by parents if they observe their child is less able and not likely to benefit from schooling. Our empirical analyses certainly suggest that when child ability is low and school quality is poor, children are more likely to be 'idle.' The most common reason the parents in our data cite for why their idle child is not in school is "the child has no interest in school." Regardless of the true activity 'idle' children are engaged in, which could be either pure 'idleness' or unpaid home production, what is important from a policy perspective is that there is a third category of child activity other than schooling and working for pay. In either case, if the goal of the policy is to increase child schooling, banning child labor may simply result in increased 'idleness' or increased involvement in home production without a commensurate increase in schooling.

Indeed, we find that separately accounting for 'idle' children is empirically important. Idle children are substantively different from those who work, those who attend school and work, and those who attend school full-time. Multinomial logit estimates further indicate that while household wealth is a significant determinant, child ability is more important in determining idleness, child labor, and schooling decisions. Even in poor households, high ability children are more likely to be in school relative to low ability children. In addition, households with moderate levels of income may let their low-ability children remain idle rather than send them to work. We also find that children in families with a family business and/or a mother who works are more likely to work while attending school at the same time. Children are also more likely to be in school than remain idle if they have access to schools with basic facilities–in particular, schools with electricity. Further specification tests suggest these results are empirically robust.

Our finding of the importance of child ability, and to some extent school quality, in determining child activities also has important policy implications. Even though we have treated child ability as exogenous in our theoretical and empirical work, it may well be that factors such as prenatal care, adequate nutrition in early childhood, access to healthcare, and overall child health contribute to the cognitive development and abilities of children.[5] Thus, any policy aiming to reduce child labor and increase child schooling should also target improvements in child ability and cognitive development through investments in the nutrition and health of poor children.

The organization of this paper is as follows. Section 2 develops our theoretical model and illustrates the policy implications of ignoring idleness. Section 3 describes the data and how our setting is fairly similar to other developing nations. Section 4 discusses the econometric specification we estimate and empirical results. Finally, Section 5 concludes with implications of our results for policy and future research.

[5] In an investigation of the nutrition-learning link using the same data from Cebu, Glewwe, Jacoby, and King (2001) found that better nourished children had higher academic achievement scores, in part because they entered school earlier and had greater learning productivity per year of schooling. They estimate that a dollar invested in an early childhood nutrition program returns at least three dollars worth of gains in academic achievement.

2 The Model

Let each household consist of one parent and one child. They live for two periods. There are no overlapping generations. Parents and children live during the same two periods. Assume that the income of the parent in the first period is y. For simplicity assume that parents do not earn anything in the second period. Each child has 1 unit of time which has to be divided between work, l, education, e, and a residual category we refer to as idleness, i. The parent has to decide how much time to allocate to these three activities. The child earns an unskilled wage of w per unit of time worked in period 1. The return from education depends on the ability, σ, of the child. If a child with ability σ devotes a fraction e of his time to education, the income of the child in the second period is $f(\sigma, e)$, where $f_1 > 0$, and $f_2 > 0$. Further, when the child goes to school, it involves a direct cost of schooling proportional to the time devoted to schooling given by $d.e$. Also, parents get a disutility from sending the child to work, which is given by $v(l)$, where $v' > 0$. Denote the total consumption of the household in period 1 by C_1 and in period 2 by C_2. The saving in the first period is denoted by S. $S < 0$ implies that the household wants to borrow to smooth consumption. Each household maximizes the following lifetime utility function:

$$U(C_1, C_2, l) = u(C_1) - v(l) + u(C_2) \tag{1}$$

where we assume no discounting of the future for simplicity.

2.1 First-Best Case

Assume that the households in this economy can borrow and lend freely in the international capital market at a given rate of interest r, which we normalize to zero. The budget constraint of the household is given as follows.

$$C_1 = y + wl - de - S; C_2 = S + f(\sigma, e) \tag{2}$$

The time constraint on the activities of the child is given by

$$l + e + i = 1 \tag{3}$$

To simplify the analysis even further, we will assume logarithmic utility from consumption and linear disutility from child labor. Further, we assume that $f(\sigma, e) = w + \theta\sigma e$, which implies that if the child does not go to school, then the earnings in the adult life are simply w. Further, the return from schooling is proportional to the time devoted to schooling and ability. Therefore, the objective function that parents seek to maximize is

$$\underset{S, 0 \le l \le 1, 0 \le e \le 1}{Max} \log(y + wl - de - S) - al + \log(S + w + \theta\sigma e) \tag{4}$$

subject to the time constraint given in (3). From the above maximization the optimal choice of S is given by

$$S = \frac{(y + wl - de) - w - \theta\sigma e}{2} \tag{5}$$

Putting the optimal value of S back in the utility function we get the following maximization problem

$$\underset{0 \le l \le 1, 0 \le e \le 1}{Max} 2\log((y + wl - de) + w + \theta\sigma e) - al - 2\log 2 \tag{6}$$

subject to the additional constraint that $l + e \le 1$. We can set up the Lagrangian for the maximization problem as follows.

$$Z = 2\log((y + wl - de) + w + \theta\sigma e) - al - 2\log 2 + \lambda(1 - l - e) + \mu(1 - e) + \phi(1 - l)$$

Now, the first order conditions are given by

$$\frac{2(\theta\sigma - d)}{(y + wl - de) + w + \theta\sigma e} - \lambda - \mu \leq 0,\ e \geq 0, \text{comp. slack} \quad (7)$$

$$\frac{2w}{(y + wl - de) + w + \theta\sigma e} - a - \lambda - \phi \leq 0,\ l \geq 0,\ \text{comp. slack} \quad (8)$$

$$1 - l - e \geq 0, \lambda \geq 0,\ \text{comp. slack} \quad (9)$$

$$1 - e \geq 0, \mu \geq 0,\ \text{comp. slack} \quad (10)$$

$$1 - l \geq 0, \phi \geq 0,\ \text{comp. slack} \quad (11)$$

The partitioning of the parameter space corresponding to different values of e, l, and i are derived in Appendix A and summarized in Figure 1. To simplify the analysis and facilitate the comparison of the first-best case with the credit-constraints case discussed below, impose the following restrictions on the parameters.

Assumption 1:$a = 2$; $\sigma > \frac{d}{\theta}$

$a = 2$ ensures that the disutility from child labor is sufficiently high to eliminate child labor in the first-best case[6], while $\sigma > \frac{d}{\theta}$ combined with $a = 2$ ensures that the returns from education are high enough to eliminate idleness. Therefore, under the above parametric restrictions all households choose $e = 1$ in the first-best case. We show below that despite this parametric restriction, credit constraints give rise to both idleness and child labor.

[6]Note that to eliminate child labor in the first-best case it is sufficient to assume that $a \geq 2$. We assume equality to facilitate comparison with the credit-constraints case.

2.2 Credit Constraints Case

Now, we assume that parents do not have access to the credit market for borrowing. Therefore, parents' maximization problem is subject to the constraint:$S \geq 0$. In this case the parent's maximization problem is

$$\underset{S\geq 0, 0\leq l\leq 1, 0\leq e\leq 1}{Max} \log(y + wl - de - S) - al + \log(w + \theta\sigma e + S)$$

subject to the aggregate time constraint : $l + e \leq 1$. Since this maximization problem is complicated, we will break it into two parts. The households for whom $S \geq 0$ is not binding will remain in the first-best situation. Therefore, for them the solutions obtained earlier remain valid. It can be shown using the information in the previous section that if (y, σ) satisfies the following inequality then the borrowing constraint is not binding.

$$y > \frac{2w}{a} + \frac{2\theta\sigma}{a} + d \tag{12}$$

The households for whom the borrowing constraint is binding solve the problem given by the following Lagrangian.

$$Z = \log(y + wl - de) - al + \log(w + \theta\sigma e) + \lambda(1 - l - e) + \mu(1 - e) + \phi(1 - l)$$

The first order conditions for the optimal choices of e and l are

$$-\frac{d}{y + wl - de} + \frac{\theta\sigma}{w + \theta\sigma e} - \lambda - \mu \leq 0, e \geq 0, \text{complementary slack} \tag{13}$$

$$\frac{w}{y + wl - de} - a - \lambda - \phi \leq 0,\ l \geq 0,\ \text{complementary slack} \tag{14}$$

$$1 - l - e \geq 0, \lambda \geq 0,\ \text{complementary slack} \tag{15}$$

$$1 - e \geq 0, \mu \geq 0,\ \text{complementary slack} \tag{16}$$

$$1 - l \geq 0, \phi \geq 0,\ \text{complementary slack} \tag{17}$$

The above conditions determine the optimal values of $e, l,$ and i for different values of parameters for the constrained households which are summarized in a table in appendix A. Note that given the parametric restriction $a = 2$, the case where $l = 1$ never obtains. Further, for the unconstrained households (defined in (12) above) we still get the first-best choice which is simply $e = 1$. Combining the cases of constrained and unconstrained households, we obtain the partitioning of the parameter space shown in Figure 2, which best illustrates our model's predictions:

1. In the poorest households ($y < w/a$), children of low ability ($\sigma < ad/\theta$) will be sent to work ($e = 0, l > 0, i > 0$).

2. Even in these poorest households where children have to work, children who are sufficiently highly able ($\sigma > ad/\theta$) will also be sent to school ($e > 0, l > 0, i \geq 0$).

3. Idleness begins to occur among households with low income ($w/a < y < 2(w/a + d)$) and low ability children ($\sigma < ad/\theta$).

4. As the ability of children from the low income ($w/a < y < 2(w/a + d)$) households increases, children go from idleness ($e = 0, l = 0, i = 1$) to some schooling and no work ($e > 0, l = 0, i > 0$), to some schooling and some work ($e > 0, l > 0, i \geq 0$), to full time schooling ($e = 1, l = 0, i = 0$). More able children from the lower households are thus sent both to school and work.

5. In contrast, more able children from slightly wealthier households ($(w/a + d) < y < 2(w/a + d)$) are directly sent to full-time schooling. As the ability of children from these households increases, children go from idleness ($e = 0, l = 0, i = 1$) to some schooling and no work ($e > 0, l = 0, i > 0$), to full-time schooling ($e = 1, l = 0, i = 0$).

6. When household wealth is sufficiently high ($y \gg 2(w/a + d)$), the borrowing constraint does not bind,

and hence the households make the first-best choice of $(e = 1, l = 0, i = 0)$.

2.3 Discussion

In our theoretical setting, being 'idle' simply means neither being in school nor engaged in paid work. Prediction (3) above notes that idleness will not be chosen by the poorest households, and begins to occur among low income households with children of low ability. This directly comes from the assumption of parental altruism and their disutility from child labor. Being less credit constrained than the poorest households, parents with low ability children would rather have them stay at home. These parents also realize their child faces a low rate of return to schooling. As the ability increases for the children in these households the first effect is an increase in schooling at the cost of 'idleness'. A further increase in ability leads to an increase in work and schooling both. Child work increases with ability for two reasons. First, since the direct cost of education is proportional to the amount of schooling, an increase in schooling increases the marginal benefit from child labor by reducing the first-period consumption. Second, as ability increases parents use child labor to smooth consumption due to the absence of borrowing opportunities. For the poorer households ($y < w/a$), these effects operate sooner so they send their children to both work and school if the child is sufficiently highly able (prediction 4), thereby skipping the 'idleness' option. For households with slightly higher income ($(w/a + d) < y < 2(w/a + d)$) even though the borrowing constraint is binding, income is high enough to make the disutility of child labor outweigh the benefit of child work (prediction 5). Therefore, when ability increases these households go from 'idleness' to some schooling with no child labor to full time schooling. When households are not credit constrained ($y > 2(w/a + d)$), given our parametric restriction in assumption 1, they choose full-time schooling for their children. (prediction 6).

2.3.1 Policy Implications

As mentioned in the introduction, the presence of 'idle' category has important policy implications. To see this clearly, suppose that in the borrowing constraint case child labor is banned. The resulting outcome is derived in the appendix and is shown in Figure 3. Comparing Figures 2 and 3, note that all the children who were engaged in full time work now become 'idle'. Therefore, banning child labor increases the pool of 'idle' children. More importantly, many poor children who combined work and schooling also become 'idle' now. This is the group in the following parameter range: $\sigma > ad/\theta$ and $y < \frac{wd}{\theta\sigma}$. In Figure 2 children in this range are working and going to school, but in Figure 3 all of them are idle. Therefore, banning child labor may not only increase 'idleness', but some of the increase may come at the cost of schooling. Thus, a ban on child labor in the presence of 'idleness' can have perverse effects on schooling. This result stands in sharp contrast to the results from models where schooling is the only alternative to child labor, and hence a ban on child labor unambiguously increases schooling.

Apart from the policy implication above which arises in the presence of the 'idleness' option, we use our theoretical model mainly to motivate the subsequent empirical analyses, and seek to highlight the importance of child ability and household wealth in jointly determining child activity decisions. These implications can certainly be derived from alternative modeling assumptions, for example, by including home production in the budget constraint. Idleness does not necessarily have to come from an assumption of parental altruism. In our analyses below, we do not seek to empirically identify the underlying motivations for idleness (altruism, incomplete labor markets, etc), but only the extent to which observable factors such as ability and household wealth determine idleness. Further, we also provide suggestive evidence of why some children are idle.

3 Data and Descriptive Statistics

3.1 The Data

The model outlined in the previous section describes an environment where credit constraints and child ability interact and play significant roles in determining child labor decisions. We explore these implications empirically using data from the Cebu Longitudinal Health and Nutrition Survey (CLHNS), which was carried out in the Metropolitan Cebu area on the island of Cebu, Philippines.

Metro Cebu is the administrative and industrial center of the Visayas (central) region of the Philippines, and includes Cebu City, the second largest city in the Philippines, and several surrounding urban and rural communities. The local economy is primarily non-agricultural, and is dominated by the trade, manufacturing, and tourism-related service sectors. It is also home to one of the busiest export processing zones in the country. The national per capita GDP in PPP terms was $3,840 in 2001. 32.7 percent of the population on Cebu island lives below the national poverty line (comparable to 36.8 percent nationally). According to the human development index developed by the United Nations–a composite of life expectancy, literacy rate, enrolment ratios, and per capita GDP, the Philippines is lodged between Paraguay and the Maldives with a rank of 85.

The CLHNS tracks a sample of 3,080 children born between May 1, 1983 and April 30, 1984, in randomly selected barangays (districts). In 1991-92 and 1994-95, follow-up surveys of mothers and children were conducted.[7]Containing a rich set of information, this survey is ideal for an empirical exploration of the above model. The surveys collected detailed information on socioeconomic and demographic household characteristics, including household assets, income and expenditures, and mother's labor supply. In addition

[7]A limited questionnaire was administered in 1996-97. A third follow-up survey was subsequently collected in 1999 and is being processed. Our study does not include data from this latest survey round. Beginning with the 1991 survey, information on the children's younger sibling of schooling age, if any, was also collected. Our sample also do not include these younger siblings.

to information on children's activities–schooling history, work, others, a test to measure IQ (nonverbal intelligence test) was also administered.[8] A survey of surrounding schools collected information on academic inputs. We then use performance on the IQ test as a measure of child ability, household expenditures to measure wealth, characteristics of schools in the area to measure school quality, as well as other controls, in examining the determinants of child activities: school, work, and idleness.

3.2 Children's Activities

We focus our analysis on the 1994-95 survey.[9] Excluding twin children, we have 2192 children for our analysis.[10] Means of key variables are reported in Table 1 by child activity. From the above model, parents allocate children's time between work for pay, schooling, and idleness. While the theoretical model implied 6 activity categories in the credit-constraint case, there are two that cannot be empirically distinguished.[11] We thus divide the sample into four identifiable mutually exclusive groups: not enrolled and not working for pay ($e = 0, l = 0, i = 1$); not enrolled and working for pay ($e = 0, l > 0, i > 0$); enrolled and working for pay ($e > 0, l > 0, i \geq 0$); and enrolled and not working for pay ($e > 0, l = 0, i \geq 0$).

Because of the age and relatively more urban location of the sample under study, there is low incidence of pure child labor. School attendance in the primary grades is quite high among Philippine children.[12] Although enrollment rates of the children in our sample (at ages 10-11) are still at 95 percent, 11 percent of children who are in school are also working for pay. Of those not in school, most (82%) are not engaged in

[8] Furthermore, in 1994-95 and a limited survey in 1996-97, Cebuano and English reading comprehension and mathematics tests were developed for the surveys based on official school curricula at various grades. Because these test scores reflect not just child ability but also school inputs, our key variable for analysis are the IQ test scores.

[9] Only the child questionnaire and achievement tests were administered in the 1996-97 survey. As a robustness check, we performed all the analyses below using the 1996-97 activity responses as dependent variable and 1994-95 household information. The results are qualitatively very similar and are available upon request.

[10] Appendix B Table 1 summarizes the attrition across these surveys. Attrition was mainly due to permanent migration out of Metro Cebu and child mortality.

[11] In particular, some school & work ($e > 0, l > 0, i = 0$) and some of each ($e > 0, l > 0, i > 0$) would be classified as school and work, while ($e > 0, l = 0, i \geq 0$) is same as full-time schooling ($e = 1, l = 0, i = 0$).

[12] Figures from UNESCO show (net) enrollment rates in primary grades in the Philippines is as high as 97.5% in 1990, 100% in 1995, and 93% in 2000.

any work for pay. We refer to this category as 'idleness' for the rest of the paper. We will also explore their various activities and reasons for non-enrollment in a later section of the paper.

The distribution of activities of our children from Metro Cebu, Philippines are comparable to children from more urban areas in other developing countries, as well. The 1994 Peru Living Standards Measurement Survey (LSMS) reports that children ages 10 to 11 in Lima have just as high enrollments, at 96 to 98 percent, and only 8 to 10 percent work (including working while in school). In urban Zimbabwe, 98.9 percent among children of the same age are in school, and less than 1 percent work (1990/91 Zimbabwe Consumer Expenditure Survey). In urban Nepal, 83 percent of children aged 10 are in school while 10 percent work (1995 Nepal LSMS).

3.3 Child and Household Characteristics

If children are being pulled out from school mainly for home production, one would expect girls to be disproportionately affected more than boys. At age 10 to 11 daughters are more likely to be helpful than sons since they can assist in baby-sitting and household chores. Contrary to this, however, majority (about two-thirds) of those not in school are actually male. Sixty eight percent of 'idle' children are male while males constitute 62 percent of children working for pay.

Patterns of schooling attendance suggest that children currently not in school are less able or less motivated. While fewer than 25 percent of children currently in school had ever repeated a grade, almost half of children currently not in school had repeated a grade by age 10 to 11. This is consistent with non-enrollees' educational attainment to date. Among those currently not in school, the last grade they report to have been enrolled in is on average more than one grade lower than those who are still in school.

Meanwhile, a nonverbal intelligence (IQ) test was administered in both the 1991 and 1994 CLHNS. There is at least a 10 percentile difference in average performance on both IQ tests across children who are in school and not in school. Non-attendees' higher grade repetition and their lower IQ test scores suggest that children who are not in school also tend to be of lower ability than those still in school. This is further illustrated in Figure 4. More children who are not in school are at the bottom end of the IQ distribution, while more children who are in school are at the top end of this distribution.

Conditional on their enrollment, children who work tend to have slightly lower IQ scores (but not significantly) than children who do not work. For instance, among children who were not in school in 1994-95, the average 1991 IQ test score for those who work was 39.8, relative to those who do not work at 41.4. Similarly, among children who were in school, the average for those who work was 51.3, relative to those who do not work at 52.2.

Family background also significantly differs by child activity. $MotherEd$ and $FatherEd$ refer to completed years of schooling of the child's mother and father, respectively. Parents of children not in school have lower levels of education, on average. Their households are also poorer, with a mean difference in per capita household expenditures (PCE) of 1 log point. More children who are not in school are at the bottom end of the PCE distribution, while more children who are in school are at the top end of this distribution. In addition, there is a slight difference among children who work and those who do not within the school enrollment decision. Among children not enrolled in school, children who work come from households with 0.56 log-points lower PCE on average than 'idle' children (though not statistically significant). Working children who are enrolled are also slightly poorer, with PCE on average 16 log points lower than enrolled children who do not work.

Table 2 best illustrates the empirical patterns that are consistent with our theoretical model. Four points are particularly noteworthy: (1) child labor is most likely to be pursued by children with low ability from low income households; (2) even in the poorest homes, schooling increases with child ability; (3) low ability children are more likely to be idle; and (4) full-time schooling increases with household wealth, holding ability constant. Table 2 thus shows the potential interaction of credit constraints and child ability in determining child activities.

In the empirical literature on child labor, additional factors such as mother's labor supply , whether or not the household owns a business, and school quality have been shown to play important roles in determining child labor decisions. Table 1 suggests that these other factors also significantly differ by child activity among Cebuano children. For instance, among children not enrolled in school, 95 percent of the children who work have working mothers ($MomWork$), while only 73 percent of idle children have working mothers. There are also more working mothers among enrolled children who work (91 percent), compared to enrolled children who do not work (70 percent). Most children engaged in child labor in the sample come from households with a family business ($FamBus$). The largest group of children with a family business are enrolled children who work (70 percent), followed by children not in school and working (52 percent), and children who do not work (41 percent-regardless of school enrollment).

3.4 Measures of School Quality

The 1994-95 CLHNS collected GPS location of households in the survey and all schools in the Metro Cebu area. We identify the nearest school for each household using these GPS coordinates.[13] In the Philippines, children do not necessarily attend their local (or nearest) school. In fact, of enrolled children in our study, slightly more than half do not attend the school nearest to them nor a school in their district or *barangay*.[14]

[13]More specifically, we calculate distances from each household to all the schools by using the Pythagorean equation and adjustments for the earth's curvature. The school associated with the minimum distance for each household is identified as their "nearest" school.

[14]Bacolod and King (2003) utilize this variation to analyze the determinants of academic achievement.

We can see from Table 1 that children who work tend to live the furthest away from their nearest school, suggesting the importance of access to a school in determining child labor.

To capture surrounding school quality, we use measures of the nearest school's resources and school-level performance on the National Elementary Assessment Test ($NEAT$). The NEAT is a test based on minimum learning competencies, and is administered to sixth grade pupils in all Philippine public and private elementary schools.

We also construct two indices to capture school resources: an index of physical facilities and of teacher resources. The physical facilities index is the sum of 10 indicators: whether the main construction material of the school is concrete; whether the school has electricity; has piped water supply; students have access to flush toilet (as opposed to latrine, open pit, or none); if no classes meet in rooms separated by temporary partitions; no multiple grade classrooms; no lack of classrooms; classes do not need to be moved/excused if it rains; if 100% of classrooms have a usable blackboard; and if the school has a library. In addition, the teacher resource index is out of 8 indicators: if the school provides a staff room; has file cabinets for records; has a telephone; has a typewriter; if teachers have access to a computer; teachers are provided chalk; teachers provided pens, pencils, crayons; and are provided with paper.

Table 1 shows that children who are currently enrolled tend to have better schools close to their home than those who are not in school. Average NEAT scores and both resource indices are slightly higher among children who are in school, although these differences are not statistically significant. We did find that differences in the facilities index were driven by whether the school has electricity or not. 80 percent of children who are in school live near schools with electricity, while only 63 percent of 'idle' children and 47 percent of working children live near schools with electricity. In the multivariate analyses below, we report results using *distance*, *electricity*, and $NEAT$ from the nearest school to capture access to and availability of school quality.

Overall, the patterns of the data from Table 1 and the distribution of children by IQ and PCE and by child activity in Figures 4-5 provide suggestive confirmation of the predictions of our theoretical model. We now turn to an empirical exploration in a multivariate setting.

4 Empirical Evidence

4.1 Determinants of Child Labor, Schooling and Idleness

The means in Table 1 and distribution of children in Table 2 suggest several potential motivations for putting children to work, school, or have them remain idle. We are particularly interested in how household wealth and child ability jointly determine this choice. To explore this in a multivariate framework and following directly from the theoretical model outlined in Section 2, suppose the parents of child i assigns a utility value to each activity choice j according to the following:

$$U_{ij} = V_{ij}(y, \sigma) + \varepsilon_{ij}.$$

V_{ij} denotes the deterministic component of $i's$ utility function from pursuing activity j, and is a function of household wealth (y) and child ability (σ), while ε_{ij} captures the effects of unmeasured choice attributes such as tastes for schooling, work, and leisure.

Following utility maximization, the probability of choosing activity k is then given by:

$$\begin{aligned}
\Pr(U_{ik} &> U_{ij}, \forall j \neq k) = \Pr(V_{ik}(y,\sigma) + \varepsilon_{ik} > V_{ij}(y,\sigma) + \varepsilon_{ij}, \forall j \neq k) \\
&= \Pr(\varepsilon_{ij} < V_{ik}(y,\sigma) - V_{ij}(y,\sigma) + \varepsilon_{ik}, \forall j \neq k)
\end{aligned}$$

Assuming ε follows an extreme value distribution, the conditional choice probabilities of pursuing each activity are given by multinomial logit formulas. We thus estimate the following multinomial logit model:

$$\Pr(Y_i = j) = F(\beta_{0j} + \beta_{1j} \ln PCE_i + \beta_{2j} \ln IQ_i + \gamma_j' X_i) \tag{18}$$

where $Y_i = j$ if choice j is chosen and j are four categories of child $i's$ activities: idleness ($e = 0, l = 0$), work only ($e = 0, l > 0$), school and work ($e > 0, l > 0$), and full-time schooling ($e > 0, l = 0$); PCE measures household wealth, IQ measures child ability; and X is a vector of other determinants of child activities.[15]

In the analyses below, we first examine the role of household wealth (PCE) and ability (IQ) as determinants of child activities. Because of the prevalence of self-employment, household expenditures is a better measure of household wealth than self-reported income. In addition, household income is mechanically correlated with child labor–if children work, total household income goes up. We thus use total annual household expenditures per household member to capture the presence of credit constraints.

In addition, we use the 1991 IQ test score (as opposed to the concurrent 1994 score). The 1991 IQ test score could be more indicative of child *innate* ability not only because of the test's design but also its timing. Because most children took the 1991 IQ test just prior to enrolling in first grade, their performance on this test is less confounded by historical school inputs than the 1994 tests. The Philippines Non-Verbal Intelligence Test is also a cognitive test designed to assess fluid ability, that is, analytical and reasoning skills. The test itself is comprised of a series of 100 cards, each of which contains drawings of five objects. The objects depicted on these cards include simple geometric shapes, local farm animals, and familiar activities of daily life in the Philippines. Children were then asked: "Which one of the 5 items is different?" As can be seen from two sample cards illustrated in Figure 5, the difficulty on this test increases as children advance through the test. The psychologists who developed the cognitive test did not develop age-specific norms,

[15] Since PCE_i, IQ_i, and the vector X_i are common across activity choices, we suppress the j notation. Our measure of ability (IQ) and household wealth (PCE) enter equation (18) in *logs* to capture the way in which ability and household wealth interact to jointly determine the activity choice. This follows directly from the logarithmic utility functions presented in Section 2.

recommending instead that the test should be used for within-sample comparative purposes (Guthrie et al. 1977).

To see how our results compare with the empirical literature, we next examine the role of a vector of other factors (X). These include other family background characteristics such as parent education, mother's labor supply interacted with child gender, the presence of a family business, and indicators of surrounding school quality.

Finally, it is important to note that our analyses capture lower bound estimates of child labor. This is because "work" in our sample is based on the respondent's answer to "Is child currently working for pay?," while a number of children are in fact likely to also be engaged in home production (without pay).

4.2 The Role of Ability and Household Wealth

The theoretical model outlined in Section 2 predicts that as child ability and income increase, children will be less likely to be idle and more likely to pursue full-time schooling. Indeed, turning to Table 3, child ability appears to be a significant determinant of child activities over and above the contribution of household wealth. Children with higher levels of ability ($LogIQ91$) and household wealth ($lnPCE$) are significantly less likely to be idle. Children with higher ability and household wealth are also significantly less likely to pursue child labor than schooling.

The negative coefficients imply that a slight increase in PCE is more likely to result in child schooling for children with the same ability level, as we expect. In addition, for households with the same wealth as measured by PCE, a slight increase in child IQ is more likely to result in child schooling. This is consistent with the negatively sloped border between the 'idleness' and positive schooling regions in our theoretical model illustrated in Figure 2. On the other hand, performance on the IQ test and household wealth as measured by PCE appear to not significantly determine the school & work versus full-time schooling option.

It may be easier to interpret the magnitude of the roles of IQ and PCE in terms of changes in predicted probabilities. Table 5 reports changes in predicted probabilities from the full version of the multinomial logit model estimated in cols (10)-(12) of Table 4. Changes in probabilities are calculated as the difference in the predicted value as the independent variable (IQ, PCE) changes while all others are held constant at their means. We calculate this change for when $LogIQ91$ and $LogPCE$ go from its minimum to its maximum (Min→Max), from -0.5 units of its mean to $+0.5$ of the mean (-+1/2), and ± 0.5 standard deviation to the mean(-+sd/2).

Going from the minimum to the maximum of $LogPCE$, children are 10.6 percent less likely to be idle, 0.4 percent less likely to work, 13.8 percent less likely to work while in school, and 24.8 percent more likely to stay in school full-time. These predicted changes are more dramatic for IQ. From the minimum to the maximum of $LogIQ$, children are 95 percent less likely to be idle and 88 percent more likely to stay in school full-time.

4.3 The Role of Other Factors

In a recent survey of the literature on child labor, Brown et. al. (2003) highlight the role of a variety of factors in determining child labor and schooling decisions. These include child age, gender, household assets such as a family enterprise, mother's work opportunities, and school availability. Child age has been found to be an important determinant in a variety of child labor studies. As the child ages, work becomes more attractive as the opportunity cost of schooling rises. Since the children in our sample come from a cohort born within a year of each other, they essentially face the same outside opportunities.

Table 4 present results examining the role of other factors influencing child labor and schooling decisions.

Note the significance of $LogIQ91$ and $LogPCE$ across the various specifications in determining the idle and work decisions as in Table 3. With the addition of controls for the presence of a family business (cols 7-9), $LogPCE$ is now also significant in determining the school & work versus full-time schooling options. This suggests that family business may have been an important omitted variable in the previous models that confounded the relationship between child labor and household income. Conditional on having a family business, children from more wealthy households are more likely to be engaged in full-time schooling than working while in school.

Both parents' education ($FatherED, MotherED$) are also in the expected direction in determining idleness–the more years of completed schooling, the more likely they are to send children to school full-time than have them be idle. Family background variables appear to have no significant impact on the other activity combinations once income is conditioned on.

Because 'idleness' is defined in our sample as not enrolled and not working for pay, female children who are not in school might be tasked with childcare and household chores. If one believed that the 'idleness' category is simply picking up unpaid home production, we would expect daughters to be more likely to be idle than sons. On the contrary we find that female children are overall less likely to be idle than engaged in full-time schooling ($female$ in cols 1,4,7,10). This is true even for girls with working mothers as shown in col 10.[16]

It is also interesting to note the positive and significant effect of mother's work ($momwork$) on the "school & work" decision (col 12)–regardless of child gender. The presence of a working mom may be a further indicator of household borrowing constraints.

[16] $momwork * female$ in col 10 is positive and significant at the 10% level, suggesting that girls with mothers who work are more likely to be idle than other daughters whose moms don't work. Overall, however, girls are less likely to be idle than boys, whether or not their mothers work. Below we discuss other pieces of evidence suggesting "idleness" is not merely picking up unpaid home production.

Whether the household owns a family business ($FamBus$) also positively and significantly affects the probability of "school & work" relative to full-time schooling. From Table 5, we see that children from households with a family business are predicted to be 8.9 percent more likely to work while in school and 9 percent less likely to be in school full-time. This suggests that this type of child labor may not be as detrimental as parents are probably supervising their children while they work for the family business.

The cost and quality of available schools should also affect child labor and schooling decisions. Distance to the nearest school captures a cost to schooling in terms of travel time. The proximity of schools ($LogDist$) do not appear to significantly affect activity decisions once school quality measures are controlled for.[17] Other indicators of school quality, such as performance on the NEAT and the indices constructed from the school survey discussed earlier, have no significant effects on child labor and schooling decisions (specifications not reported).

On the other hand, an indicator variable of whether the nearest school has electricity significantly affects the 'idleness' decision. Children living near a school that has electricity are less likely to be idle than be in school full-time. This finding is consistent with the education production function analysis in Bacolod and Tobias (2003) using the same data. They find that schools with electricity perform much better in the production of student-level achievement growth than schools without electricity.[18]

The importance of having electricity in schools may be due to the humid weather in the Philippines. Of course electricity may also be capturing other school resources and community characteristics that are unmeasured in our analysis. For instance, if the local school has no electricity then most likely the residents

[17] Without controls for measures of school quality, $LogDist$ is significant for the "work" option. The further the nearest school is, the more likely the child is to work full-time. In the interest of discussing what it is about school quality that drive these results, we present Table 3 instead.

[18] Other education production function studies in developing countries (e.g., Harbison and Hanushek 1992) find support for the role of minimal basic facilities. For instance, Glewwe and Jacoby's (1994) study of Ghana found that the single most important school characteristic in determining reading and math test scores was leaking roofs, as schools would have to close when it rained.

are also not connected to the grid. Children could conceivably prefer to be 'idle' than be in school under such conditions.

Table 6 reports test statistics for equality of coefficients across these activity decisions. IQ and PCE have significantly different effects on the "work" versus "school & work" decisions and on the 'idleness' and "school & work" decisions. Among the family background variables, mother's labor supply has the most significant unequal effects in determining child labor and schooling decisions. Parent education and having a family business also have unequal effects on 'idleness' versus "school & work" options.

These results are also robust to a variety of specification tests. Hausman tests indicate our multinomial logit model does not violate the independence of irrelevant alternatives assumption. Furthermore, a more general Lagrange multiplier test of our multinomial logit against any generalized extreme value model with random errors or random parameters as an alternative leads us to favor our multinomial logit model. We discuss these efforts in more detail in Appendix C.

4.4 "Idleness" or Home Production?

If children are not in school and are not working, what are they doing? Because of the structure of survey questionnaires such as the CLHNS, home production is typically not classified as "work." In some cases, children who are 'idle' may actually be engaged in significant household chores, such as baby-sitting. Children may also be idle because of imperfect labor markets. Outside work opportunities for these children may not exist, while their parents cannot afford to send them to school. The importance of ability in the previous section suggests that comparative advantage may also play a role in determining idleness. If parents perceive their child's return to education to be low, they will pull them from school.

CLHNS asked the mothers of non-enrolled children for the primary reason their child was not attending school. Table 7 reports their responses by child labor. These self-reported responses certainly highlight the notion of 'idleness' as a significant category of child activity. The child having "no interest in school" is the most prevalent reason for non-enrollment. Although this evidence can only be taken as suggestive at best, this reasoning suggests most 'idle' children are not in school because their parents perceive their return to schooling to be low. This may be because of perceived low ability or bad school quality. These children are thus really idle in the sense that they are not engaged in any type of production.

Note that the second most prevalent reason for child labor is financial problems. Among 'idle' children, the second prevalent reason is child illness, suggesting the importance of health in determining children's activities and human capital accumulation, a point made by Strauss and Thomas (1998). It may be that children are idle because their physical and/or mental health require special needs that the local schools are unable to provide.[19]

As a whole, only less than 20 percent indicate potential borrowing constraints and imperfect labor markets as the primary consideration for non-enrollment–11 percent cite financial problems, 4.3 percent cite baby-sitting, and 2.6 percent indicate working in the family business. Other reasons include "the child was gambling too much," "child is scared of teacher," "child knows nobody in school," "child was late for registration," and "school too far." All these reasons indicate idle children may not have access to good school quality.

It is worth re-iterating that what is really important from the policy point of view is the recognition of a third category of child activity, whether it be 'idleness' or home production. In either case, if the goal of policy is to increase child schooling, banning child labor may end up reducing child schooling.

[19] In an effort to see if our results are primarily being driven by mentally handicapped children or children who particularly require special education, we re-estimated our multinomial logit models excluding children in the bottom 5 percent of the IQ distribution. Our results are unchanged in both the direction and magnitude of the marginal effects.

5 Conclusion

We have shown that child ability and household wealth jointly and significantly determine child labor and schooling decisions. Consistent with the predictions of our theoretical model, poor households with high ability children are more likely to send them to school than poor households with low ability children. Also, there is some evidence that households with moderate levels of income may let their low-ability children remain 'idle' rather than sending them to work.

The roles of ability and household wealth are particularly significant in terms of predicted probabilities. Going from the minimum to the maximum range of our measure of household wealth, children are 10.6 percent less likely to be idle, 0.4 percent less likely to engage in child labor, 13.8 percent less likely to work while in school, and 24.8 percent more likely to stay in school full-time. Even more striking, from the minimum to the maximum of our measure of ability, children are 95 percent less likely to be idle and 88 percent more likely to stay in school full-time. Ability seems to be far more important than household wealth in determining child non-enrollment in school.

In addition, we find that children in families with a family business and/or a mother who works are more likely to work while attending school at the same time. Access to good school quality is also important. Living close to schools with minimal basic facilities–in particular, schools with electricity–makes children more likely to be in school full-time than remain idle. Various specification tests indicate that these results are empirically robust.

The setting of our data limits the examination of pure child labor decisions, however. Due to both the age and the more urban location of the sample under study, most children are still enrolled in school.

Nevertheless, our study leads to certain implications for the international community. Metro Cebu, Philippines is not that different from most other urban areas in developing countries. Our children's enrollment and child labor rates are comparable to urban children of the same age in Peru, Nepal, and Zimbabwe.

Given our finding of the importance of child ability in determining idleness, further investigation is required before calls are made for banning child labor across the board. These calls are often motivated by concerns over hazardous and exploitative conditions working children are subjected to. However, as our theoretical model formally shows, once child ability is taken into account a ban on child labor may just increase the pool of idle children from two margins–children who were working full time as well as children who worked while attending school.

While we have treated child ability as exogenous in our theoretical and empirical models, policies might instead be better directed towards improving this human capital stock. Poverty and lack of nutrition potentially have serious adverse impacts on the abilities and human capital stock of children. Therefore, any policy aiming to reduce child labor and increase child schooling should also focus on ways to improve child ability through investments in nutrition and health of poor children and through investments in school quality.

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6 Appendix A: Partitioning of Parameter Space

6.1 First-Best Case

Depending on the value of the Lagrangian multipliers λ, μ, and ϕ, we get the following 4 possibilities.

Case I: $\lambda = 0, \mu = 0$, and $\phi = 0$

In this case (7) and (8) become

$$\begin{aligned} \frac{2(\theta\sigma - d)}{(y + wl - ed) + w + \theta\sigma e} &\leq 0 \qquad (19) \\ \frac{2w}{(y + wl - ed) + w + \theta\sigma e} - a &\leq 0 \qquad (20) \end{aligned}$$

Now, we have 4 sub-cases depending on whether the above two weak inequalities are equalities or strict inequalities. Since $\lambda = 0$ implies $e + l < 1$, we have $i > 0$ in all the cases below.

Case I.a both (19) and (20) are equalities implying $e > 0$ and $l > 0$.

The parameter range for this case is $\sigma = \frac{d}{\theta}$, and $\frac{2w}{a} - 2w < y < \frac{2w}{a} - w$. The value of l is given by

$$l = \frac{2}{a} - 1 - \frac{y}{w}$$

while $e \in (0, 1)$ is such that $e + l < 1$.

Case I.b both (19) and (20) are strict inequalities implying $e = 0$ and $l = 0$ and $i = 1$. In order for (19) to be a strict inequality we need $\sigma < \frac{d}{\theta}$. Further, for (20) to be a strict inequality at $e = 0$ and $l = 0$, the condition is $y > \frac{2w}{a} - w$.

Case I.c (19) is a strict inequality and (20) is an equality implying $e = 0$ and $l > 0$. The range of parameters for this case is given by $\sigma < \frac{d}{\theta}$ and $\frac{2w}{a} - 2w < y < \frac{2w}{a} - w$, and the value of l is given by

$$l = \frac{2}{a} - 1 - \frac{y}{w}$$

Case I.d (19) is an equality and (20) is a strict inequality implying $e > 0$ and $l = 0$. The range of parameters for this case is given by $\sigma = \frac{d}{\theta}$ and $y > \frac{2w}{a} - w$ and $e \in (0, 1)$.

Case II: $\lambda > 0, \mu = 0$, and $\phi = 0$

In this case $\lambda > 0$ implies $e + l = 1$, which combined with $\mu = 0$, and $\phi = 0$ implies $e \in (0, 1)$ and $l \in (0, 1)$. Therefore, the first order conditions for this case are

$$\begin{aligned} \frac{2(\theta\sigma - d)}{(y + wl - ed) + w + \theta\sigma e} &= \lambda \\ \frac{2w}{(y + wl - ed) + w + \theta\sigma e} - a &= \lambda \end{aligned}$$

From the above two conditions we can derive the following range of parameters for this case.

$$\begin{aligned} \sigma &> \frac{d}{\theta} \\ y &< (w + d - \sigma\theta)(\frac{2}{a} + 1) - 2w \end{aligned}$$

Case III: $\lambda > 0, \mu > 0$, and $\phi = 0$

In this case $\lambda > 0$ and $\mu > 0$ together imply $e = 1$ and $l = 0, i = 0$. The first order conditions for this case can be written as

$$\begin{aligned} \frac{2(\theta\sigma - d)}{(y - d) + w + \theta\sigma} &= \lambda + \mu \\ \frac{2w}{(y - d) + w + \theta\sigma} - a &< \lambda \end{aligned}$$

From the above two conditions we can derive the following range of parameters for this case is.

$$
\begin{aligned}
\sigma &> \frac{d}{\theta} \\
y &\geq (w+d-\sigma\theta)(\frac{2}{a}+1)-2w
\end{aligned}
$$

Case IV: $\lambda > 0, \mu = 0$, and $\phi > 0$

In this case $\lambda > 0$ and $\phi > 0$ together imply $l = 1$ and $e = 0, i = 0$. The first order conditions for this case can be written as

$$
\begin{aligned}
\frac{2(\theta\sigma - d)}{(y+w)+w} &< \lambda \\
\frac{2w}{(y+w)+w} - a &= \lambda + \phi
\end{aligned}
$$

From the above two conditions we can derive the following range of parameters for this case.

$$
\begin{aligned}
\sigma &\leq \frac{d}{\theta} \\
y &< \frac{2w}{a} - 2w
\end{aligned}
$$

The partitioning of the parameter space derived above is depicted in Figure 1.

6.2 Credit-Constraint Case

Again, as in the first-best case, we have the following 4 cases depending on the value of the Lagrangian multipliers: λ, μ, and ϕ.

Case I: $\lambda = 0, \mu = 0$, and $\phi = 0$

In this case (13) and (14) become

$$
\frac{\theta\sigma}{(w+\theta\sigma e)} - \frac{d}{(y+wl-ed)} \leq 0 \tag{21}
$$

$$
\frac{w}{(y+wl-ed)} - a \leq 0 \tag{22}
$$

Now, we have 4 possibilities depending on whether the above two weak inequalities are equalities or strict inequalities. Since $\lambda = 0$ implies $e + l < 1$, we have $i > 0$ in all the cases below.

Case I.a both (21) and (22) are equalities implying $e > 0$ and $l > 0$ and the values of e and l are given by

$$
\begin{aligned}
e &= \frac{w(\theta\sigma - ad)}{ad\theta\sigma} \\
l &= \frac{1}{a} + \frac{\theta\sigma - ad}{a\theta\sigma} - \frac{y}{w}
\end{aligned}
$$

Now, $e > 0$ implies $\sigma > \frac{ad}{\theta}$, $l > 0$ implies $y < \frac{2w}{a} - \frac{wd}{\theta\sigma}$ and $e < 1$ implies $\sigma < \frac{adw}{\theta(w-ad)}$ and $l < 1$ implies $y > \frac{2w}{a} - w - \frac{wd}{\theta\sigma}$. Finally, $e + l < 1$ implies $y > \frac{2w}{a} - w - \frac{wd}{\theta\sigma} + w^2(\frac{\theta\sigma - ad}{ad\theta\sigma})$. Since $\sigma > \frac{ad}{\theta}$ in this case, the range of parameters for this case are

$$
\begin{aligned}
\frac{ad}{\theta} &< \sigma < \frac{adw}{\theta(w-ad)} \\
&\frac{2w}{a} - w - \frac{wd}{\theta\sigma} + w^2(\frac{\theta\sigma - ad}{ad\theta\sigma}) < y < \frac{2w}{a} - \frac{wd}{\theta\sigma}
\end{aligned}
$$

Case I.b both (21) and (22) are strict inequalities implying $e = 0$ and $l = 0$ and $i = 1$. In order for (21) to be a strict inequality $e = 0$ and $l = 0$ we need $y < \frac{wd}{\theta\sigma}$ and for (22) to be a strict inequality at $e = 0$ and $l = 0$ the condition is $y > \frac{w}{a}$. Therefore, the range of parameters for this case are

$$\frac{w}{a} < y < \frac{wd}{\theta\sigma}$$

Case I.c (21) is a strict inequality and (22) is an equality implying $e = 0$ and $0 < l < 1$. The range of parameters for this case is given by

$$\sigma < \frac{ad}{\theta} \text{ and } \frac{w}{a} - w < y < \frac{w}{a}$$

Case I.d (21) is an equality and (22) is a strict inequality implying $0 < e < 1$ and $l = 0$. The value of e from the equality in (21) is obtained as

$$e = \frac{\theta\sigma y - wd}{2\theta\sigma d}$$

Therefore, in order for $e > 0$ we need $y > \frac{wd}{\theta\sigma}$ and for $e < 1$ we need $y < \frac{wd}{\theta\sigma} + 2d$. Finally, from the strict inequality in (22) we get $y > \frac{2w}{a} - \frac{wd}{\theta\sigma}$. Thus, the parametric restrictions for this case are

$$\max\{\frac{wd}{\theta\sigma}, \frac{2w}{a} - \frac{wd}{\theta\sigma}\} < y < \frac{wd}{\theta\sigma} + 2d$$

Case II: $\lambda > 0, \mu = 0$, and $\phi = 0$

In this case $\lambda > 0$ implies $e + l = 1$, which combined with $\mu = 0$, and $\phi = 0$ implies $e \in (0, 1)$ and $l \in (0, 1)$. Therefore, the first order conditions for this case are

$$\frac{\theta\sigma}{(w + \theta\sigma e)} - \frac{d}{(y + wl - ed)} = \lambda \tag{23}$$

$$\frac{w}{(y + wl - ed)} - a = \lambda \tag{24}$$

For a given e the above two imply the following necessary restrictions on the parameters.

$$\frac{wd}{\theta\sigma} + 2ed - (1 - e)w < y < \frac{w}{a} + ed - (1 - e)w$$

From (23) and (24) we can obtain the values of e and λ, by substituting out l using $l = 1 - e$. Further, e must satisfy $e \in (0, 1)$, which imposes the following restrictions on parameters.

$$\frac{w(d + (a - 1)w - \theta\sigma)}{aw + \theta\sigma} < y < \frac{(w + d)(w + \theta\sigma)}{aw + a\theta\sigma + \theta\sigma} + d$$

Furthermore, (23) and (24) also imply $\sigma > \frac{adw}{\theta(w-ade)}$. Since $e > 0$, a necessary condition for this case to obtain is $\sigma > \frac{ad}{\theta}$. Finally, by substituting for e the condition $y < \frac{w}{a} + ed - (1 - e)w$ becomes $\frac{2w}{a} - w - \frac{wd}{\theta\sigma} + w^2(\frac{\theta\sigma - ad}{ad\theta\sigma}) > y$. Therefore, the parameter range for this case is non-overlapping with the parameter range for the case $e > 0, l > 0, i > 0$.

Case III: $\lambda > 0, \mu > 0$, and $\phi = 0$

In this case $\lambda > 0$ and $\mu > 0$ together imply $e = 1$ and $l = 0, i = 0$. The first order conditions for this case can be written as

$$\frac{\theta\sigma}{(w + \theta\sigma)} - \frac{d}{(y - d)} = \lambda + \mu \tag{25}$$

$$\frac{w}{(y - d)} - a < \lambda \tag{26}$$

From (25) we get a necessary condition for this case to obtain as

$$y \geq \frac{wd}{\theta\sigma} + 2d$$

Further, (25) and (26) together yield another necessary condition given below

$$y \geq \frac{(w+d)(w+\theta\sigma)}{aw + a\theta\sigma + \theta\sigma} + d$$

Therefore, a condition for this case to obtain can be written as

$$y \geq Max\{\frac{(w+d)(w+\theta\sigma)}{aw + a\theta\sigma + \theta\sigma} + d, \frac{wd}{\theta\sigma} + 2d\}$$

Case IV: $\lambda > 0, \mu = 0$, and $\phi > 0$

In this case $\lambda > 0$ and $\phi > 0$ together imply $l = 1$ and $e = 0, i = 0$. The first order conditions for this case can be written as

$$\begin{aligned} \frac{\theta\sigma}{w} - \frac{d}{y+w} &< \lambda \\ \frac{w}{y+w} - a &= \lambda + \phi \end{aligned}$$

From the above two conditions we can derive the following range of parameters for this case.

$$y < \min\{\frac{w}{a} - w, \frac{wd}{\theta\sigma} - w\}$$

Therefore, we get the following partitioning of the parameter space for different values of e, l, and i.

$e = 1, l = 0, i = 0$	if	$y \geq Max\{\frac{(w+d)(w+\theta\sigma)}{aw+a\theta\sigma+\theta\sigma} + d, \frac{wd}{\theta\sigma} + 2d\}$
$e > 0, l > 0, i > 0$	if	$\frac{adw}{\theta(w-ad)} > \sigma > \frac{ad}{\theta}$, $y < (\frac{2w}{a} - \frac{wd}{\theta\sigma})$, and
		$y > \frac{2w}{a} - w - \frac{wd}{\theta\sigma} + w^2(\frac{\theta\sigma - ad}{ad\theta\sigma})$
$e > 0, l > 0, i = 0$	if	$\frac{w(d+(a-1)w-\theta\sigma)}{aw+\theta\sigma} < y < \frac{(w+d)(w+\theta\sigma)}{aw+a\theta\sigma+\theta\sigma} + d$, and
		$\frac{wd}{\theta\sigma} + 2ed - (1-e)w < y < \frac{w}{a} + ed - (1-e)w$
$e > 0, i > 0, l = 0$	if	$Max\{\frac{wd}{\theta\sigma}, \frac{2w}{a} - \frac{wd}{\theta\sigma}\} < y < \frac{wd}{\theta\sigma} + 2d$
$e = 0, l = 0, i = 1$	if	$\sigma < \frac{ad}{\theta}$, and $\frac{w}{a} < y < \frac{wd}{\theta\sigma}$
$e = 0, l > 0, i > 0$	if	$\sigma < \frac{ad}{\theta}$, and $\frac{w}{a} - w < y < \frac{w}{a}$
$e = 0, l = 1, i = 0$	if	$y < Min\{\frac{wd}{\theta\sigma} - w, \frac{w}{a} - w\}$

6.3 Implications of banning child labor in the credit-constraint case

Now the households maximize the following

$$\underset{0 \leq e \leq 1}{Max} \log(y - ed) + \log(w + \theta\sigma e)$$

The first order condition for the above maximization is

$$\frac{-d}{y - ed} + \frac{\theta\sigma}{w + \theta\sigma e} \leq 0 \tag{27}$$

From (27) we can easily derive the following results.

$$\begin{aligned} \text{If } y &\leq \frac{wd}{\theta\sigma} \text{ then } e = 0 \text{ and } i = 1 \\ \text{If } \frac{wd}{\theta\sigma} &< y < \frac{wd}{\theta\sigma} + 2d \text{ then } 0 < e < 1 \text{ and } i > 0 \\ \text{If } y &\geq \frac{wd}{\theta\sigma} + 2d \text{ then } e = 1 \text{ and } i = 0 \end{aligned}$$

Since the people for whom the borrowing constraint does not bind, never choose positive amount of child labor, their behavior remains unchanged after the ban is imposed. Therefore, the partitioning of the parameter space in this case is the one depicted in Figure 3.

7 Appendix B: Sample Selection and Attrition from the CLHNS

Live Births in 33 Sample Barangays of Metro Cebu		3,289	
Of which:	Twin Births	27	(0.8%)
	Refusals	97	(2.9%)
	Missed by Survey (discovered later)	58	(1.8%)
	Birth Interview Too Late	22	(0.7%)
Live Births in Metro Cebu with Birth Interview		3,085	
Of which:	Migrated Out of Metro Cebu by Age 2	318	(10.3%)
	Child Died by Age 2	156	(5.1%)
	Refusal (at later date)	50	(1.6%)
Still in Sample When Child is 2 years old		2,561	
Of which:	Migrated Out of Metro Cebu by Age 8	155	(6.1%)
	Could not find child at Age 8	137	(5.3%)
	Child Died by Age 8	38	(1.5%)
Still in Sample When Child is 8 yrs old (1991-92)		2,231	
Of which:	Migrated Out/Could Not Find	31	(1.4%)
	Child Died	8	(0.4%)
Still in Sample When Child is 11 yrs old (1994-95)		2,192	
Of which:	Never Enrolled in School	9	(0.4%)

8 Appendix C: Specification Tests

We first conduct Hausman tests for the independence of irrelevant alternatives (IIA) assumption. We find that we cannot reject the null that the odds are independent of other alternatives. However, Small-Hsiao tests for IIA lead us to reject the validity of the IIA assumption. These results may not be surprising given that the tests require estimating the model on a subset of the alternatives, using only a small portion of the data in some cases. As further robustness checks to our specification, we conduct the following more general test computed over the full set of choices and observations.

Small (1994) proposes several tests for the null hypothesis of multinomial logit against any particular generalized extreme value (GEV) model as an alternative hypothesis. Alternatives can thus include different forms of nested logit. The test we carry out can also be motivated as a Lagrange Multiplier test against a random error components specification (also called mixed logit models):

$$U_{ij} = \beta_j' x_{ij} + [\eta_{ij} + \varepsilon_{ij}],$$

where x_{ij} is a vector of observables for person i and activity choice j; β_j are the parameters of interest; η_{ij} is a random term with mean zero but whose distribution over ij depends on underlying parameters and observed data; and ε_{ij} is random with zero mean that is independent and identically distributed.

The test is carried out by adding to the variables x_{ij} a set of pseudovariables z_{ij}, re-estimating the model, and conducting a test for the joint significance of the z variables. In practice, we construct our pseudovariables as described by Brownstone (2001):

$$z_{ij} = (x_{ij} - x_{iC})^2, \text{ with } x_{iC} = \sum_{k \neq j} x_{ik} P_{ik}$$

and P_{ik} is the predicted conditional logit probability.

In our case, because attributes x are not choice-specific, the multinomial logit model (equation (18) in the paper) we estimate is equivalent to the conditional logit. After constructing choice-specific z's, we reestimate the conditional logit model including these artificial variables:

$$\Pr(y_{ij} = 1 \mid x, z) = F(x_{ij}\beta + z_{ij}\delta).$$

We reject the null hypothesis of our original multinomial logit in favor of some specification with random coefficients on x or random error components if the coefficients on the artifical variables (δ) are significantly different from zero. Because this test also detects the presence of significant error components, it is a more general test of the IIA assumption in our multinomial logit model.

We construct Wald test statistics of the joint significance of our z variables and report these below for each choice:

	Test Statistic	p-value	Conclusion
Idleness	$\chi^2(12) = 12.05$	0.28	fail to reject H_o
Work	$\chi^2(10) = 7.09$	0.63	fail to reject H_o
School & Work	$\chi^2(11) = 9.11$	0.52	fail to reject H_o
School	$\chi^2(12) = 6.04$	0.81	fail to reject H_o

As a further check, we also estimated bivariate probit models as an alternative specification. The specification is

$$\begin{aligned}
work_i^* &= \delta_1' x_i + \epsilon_{1i}, \;\; work_i = 1 \text{ if } work_i^* > 0, \; 0 \text{ o.w.} \\
school_i^* &= \delta_2' x_i + \epsilon_{2i}, \;\; school_i = 1 \text{ if } school_i^* > 0, \; 0 \text{ o.w.} \\
E(\epsilon_{1i}) &= E(\epsilon_{2i}) = 0, \;\; Var(\epsilon_{1i}) = Var(\epsilon_{2i}) = 1, \\
Cov(\epsilon_{1i}, \epsilon_{2i}) &= \rho.
\end{aligned}$$

The bivariate probit model take into account non-zero correlation (ρ) across the schooling and work equations. Our estimates of the bivariate probit model lead to similar qualitative results as the multinomial logit estimates presented in the paper. These are also available from the authors on request. In terms of maximized value of the log-likelihood, multinomial logit (-1071.539) is slightly better than bivariate probit (-1073.798), although this is not a formal likelihood ratio test since both models are not nested in the other.

Because the estimate of the correlation parameter was also not significantly different from zero [H_o:$\rho = 0$, $\chi^2(1) = 1.414$, p-value= 0.23], the multinomial logit model is our preferred specification.

Finally, we perform the same set of analyses using the 1996-97 limited survey. In particular, we use responses to the child questionnaire in 1996-97 to code child activity, and the 1994-95 household and school survey responses for the independent variables. As expected, since the index children are now aged 12-13, a greater proportion are no longer in school. Because information on outside paid work can only be gleaned from the time diary portion of the questionnaire (as opposed to the household schedule of market activities in the 1994-95 survey), we can only identify less than 1 percent of children pursuing child labor:

Activity in 1996-97	Freq (%)
Not in school & zero work hours on typical schoolday	193 (9%)
Not in school & positive work hours on typical schoolday	13 (0.6%)
In school & positive work hours on typical schoolday	263 (12.4%)
Full-time schooling	1650 (78%)

The 1996-97 analyses produced qualitatively similar results to those discussed more extensively in the paper. These results are also available on request from the authors.

Figure 1: partitioning of parameter space in the first-best case

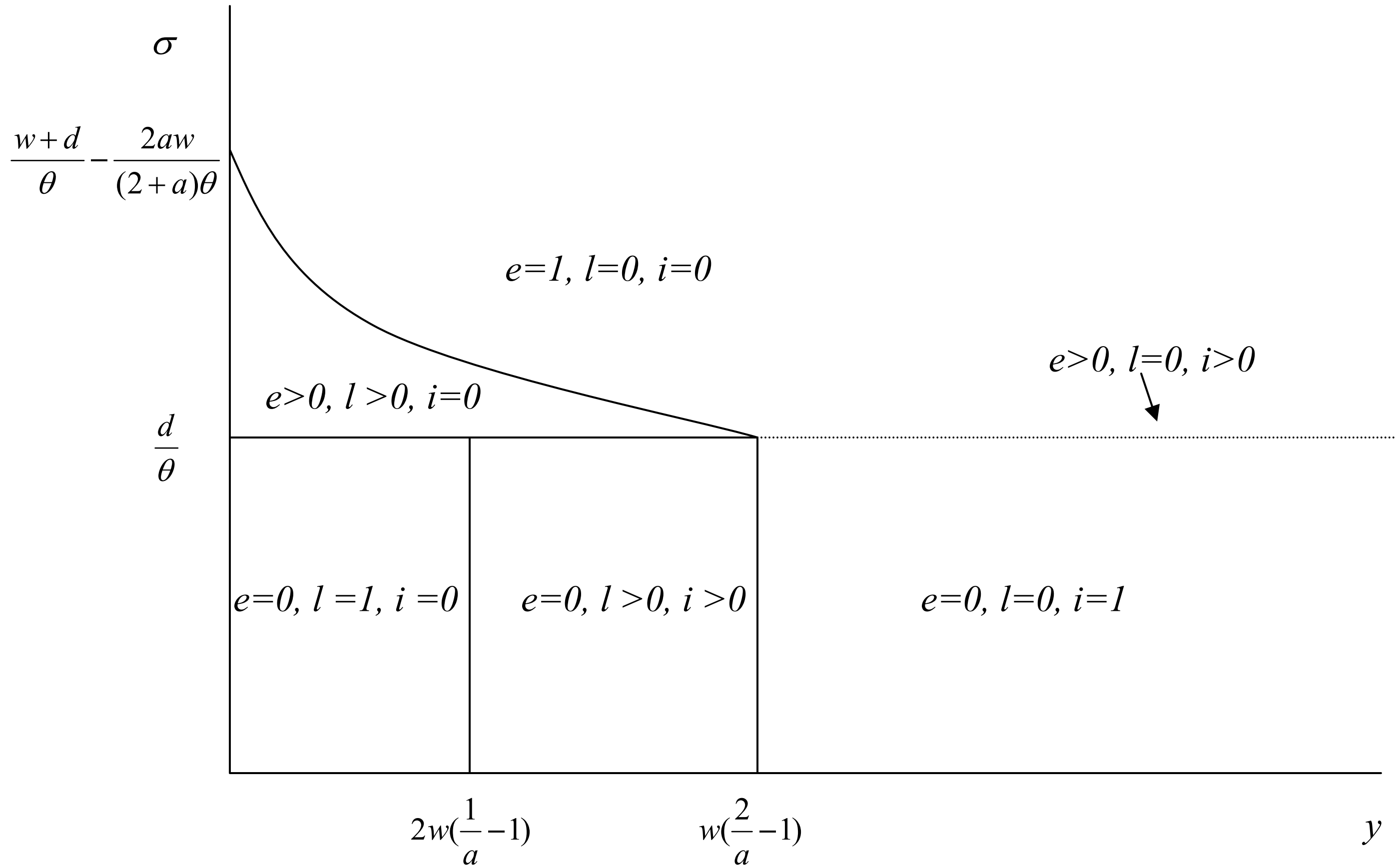


Figure 2: partitioning of parameter space in the credit-constraint case

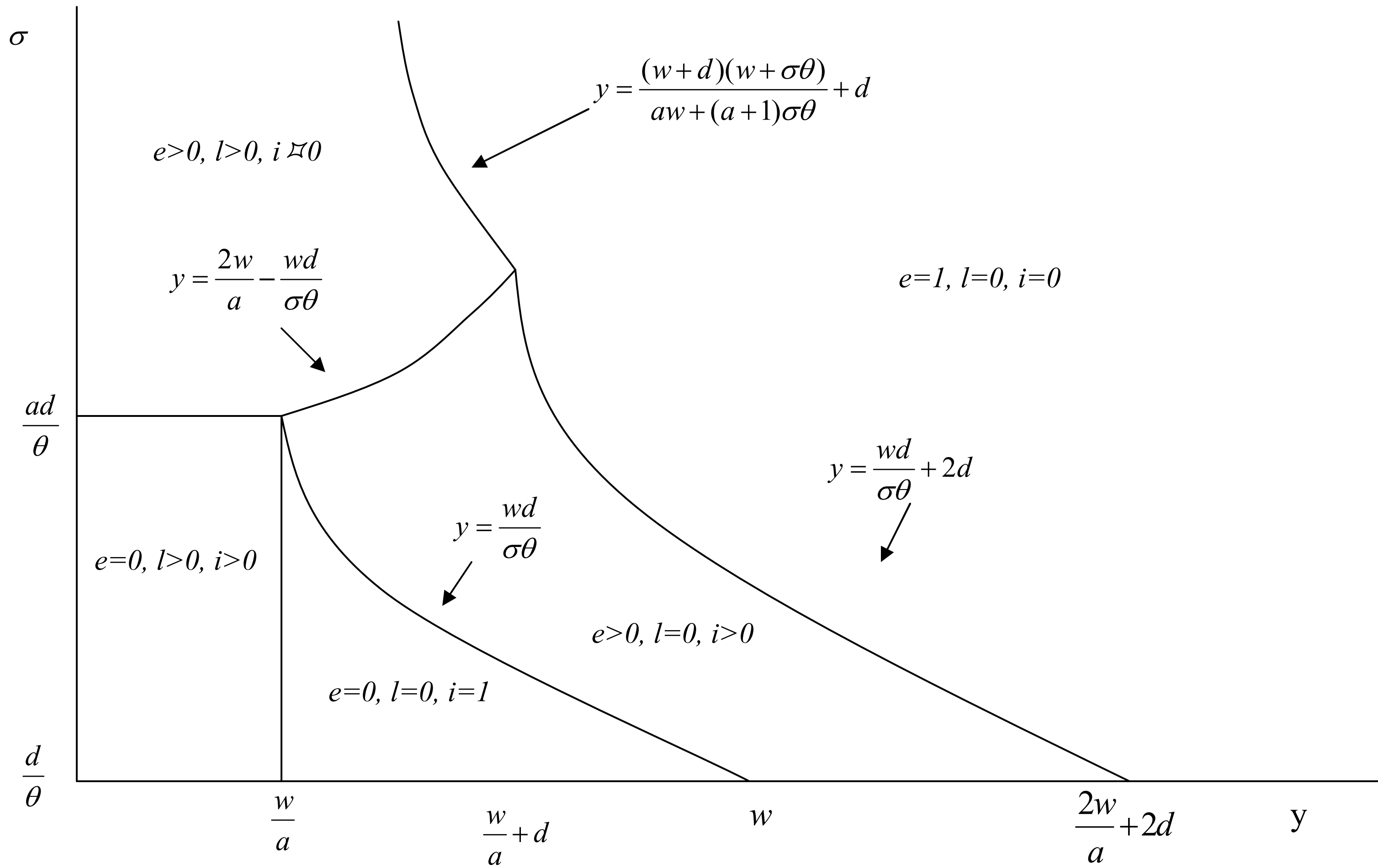
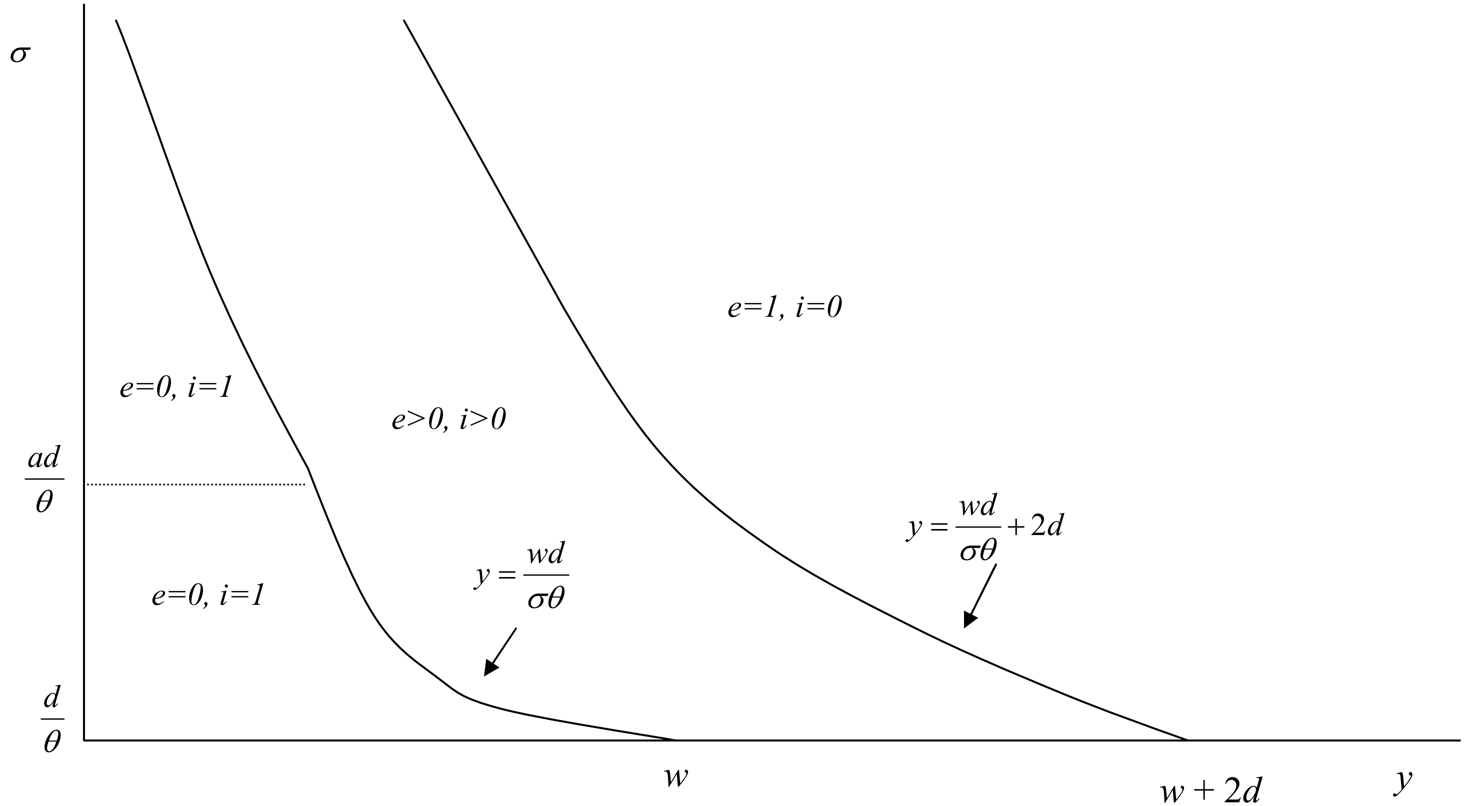
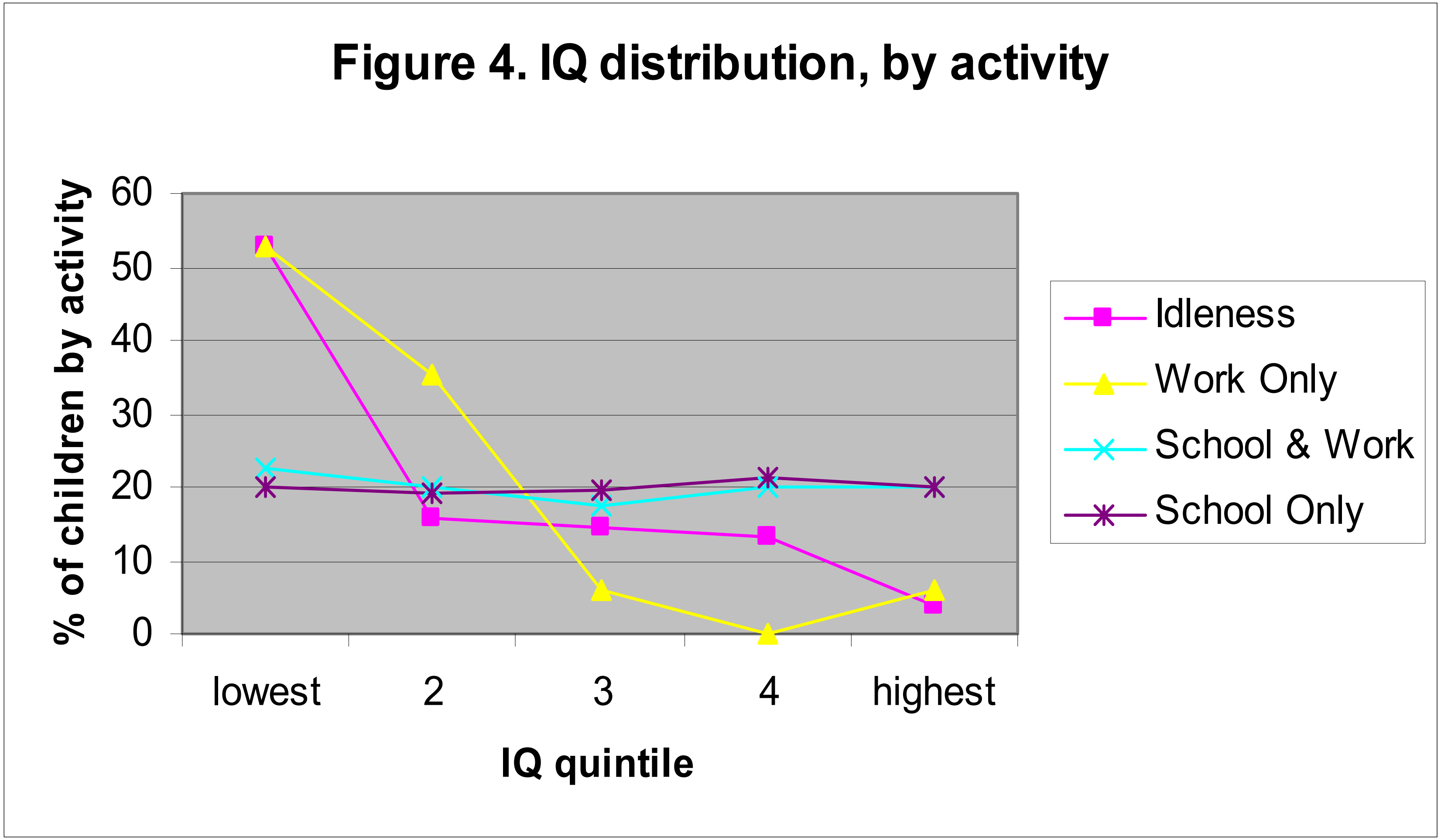


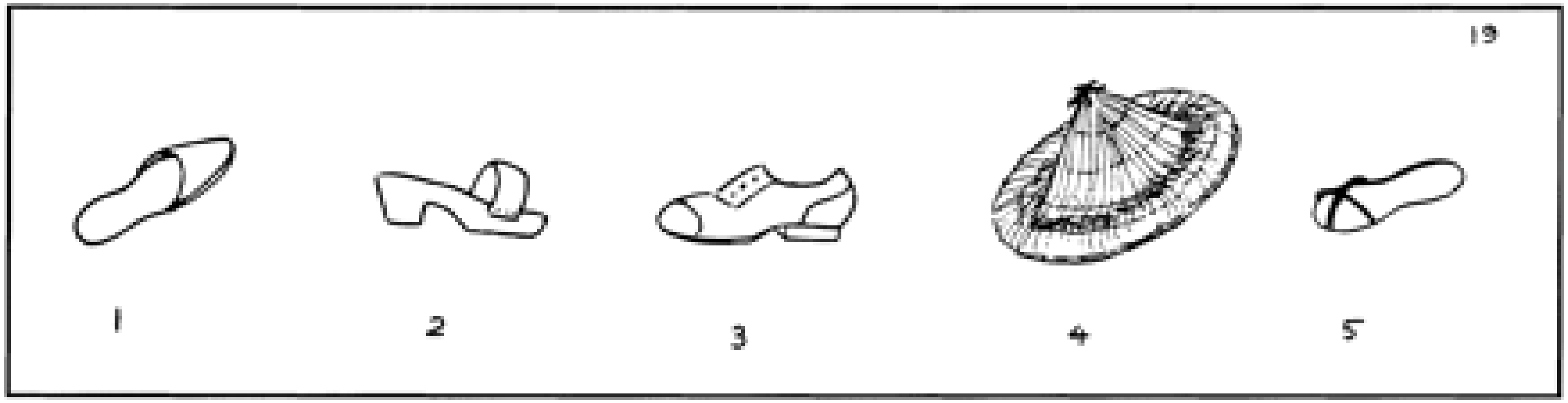
Figure 3: Implications of banning child labor

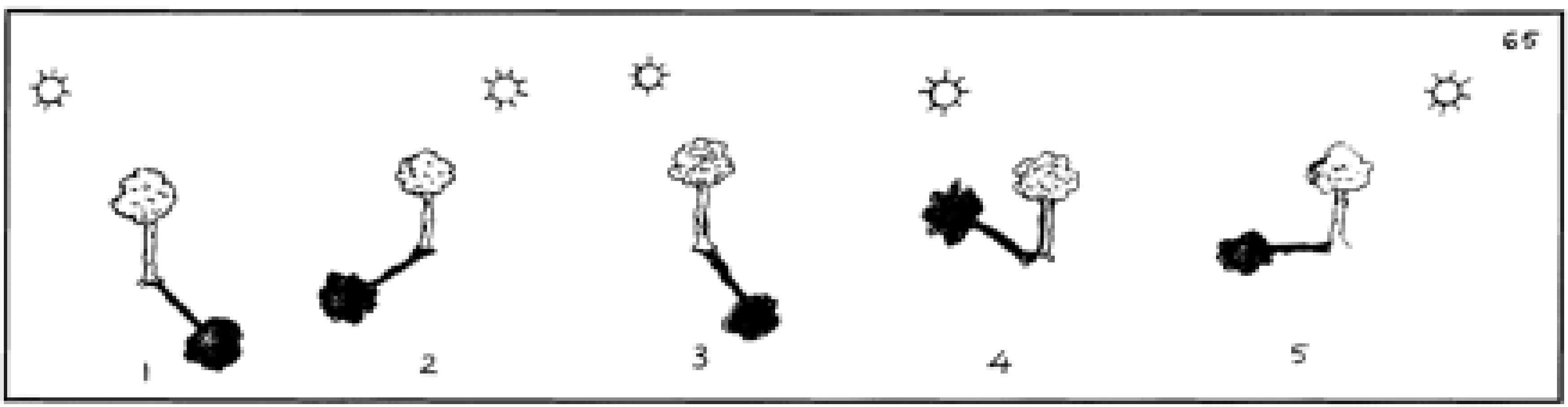




Source: CLHNS. Percentages add up to one within activity.

Figure 5. Sample questions from the Phillippines Non-Verbal Intelligence (IQ) Test.





Note: Test questions were asked in series of 100 cards that increase in difficulty. Above are cards number 19 and 65. Children were asked: Which one of the 5 items is different? Pictures from Mendez & Adair (1999).

TABLE 1. Descriptive Statistics of Key Variables, by Child Activity

	Not Enrolled in School		Enrolled In School	
	No Work	Working	Working	No Work
No. of children	95 (4.3%)	21 (1%)	228 (10.4%)	1848 (84.3%)
Age in 1994	10.28 (0.45)	10.33 (0.48)	10.30 (0.46)	10.27 (0.44)
Male	0.68 (0.47)	0.62 (0.50)	0.46 (0.50)	0.52 (0.50)
Grade Level[1]	2.66 (1.19)	2.60 (1.1)	4.11 (1.07)	4.18 (0.92)
Repeated Grade	0.48 (0.50)	0.45 (0.51)	0.22 (0.42)	0.23 (0.42)
1991 IQ	41.39 (13.45)	39.82 (12.32)	51.30 (12.35)	52.15 (12.09)
1994 IQ	55.59 (11.35)	53.70 (12.09)	69.24 (11.31)	69.73 (11.22)
FatherED	4.94 (3.28)	4.47 (3.22)	7.48 (3.70)	7.88 (3.99)
MotherED	4.75 (3.10)	4.26 (2.23)	7.31 (3.75)	7.65 (3.89)
MomWork	0.73 (0.45)	0.95 (0.23)	0.91 (0.29)	0.70 (0.46)
Log PCE[2]	6.33 (1.46)	5.77 (1.54)	7.25 (1.33)	7.41 (1.36)
FamBus[3]	0.41 (0.49)	0.52 (0.51)	0.70 (0.46)	0.41 (0.49)
Characteristics of school nearest to household:				
Distance (meters)	559.8 (383.7)	702.4 (379.1)	437.2 (344.9)	437.8 (375)
Facilities Index[4]	7.46 (1.86)	7.18 (1.55)	7.85 (1.56)	7.92 (1.62)
Resource Index[5]	4.0 (2.19)	3.88 (2.45)	4.27 (1.89)	4.54 (1.85)
Has electricity	0.63 (0.49)	0.47 (0.51)	0.80 (0.40)	0.82 (0.38)
NEAT[6]	135.8 (84.1)	110.8 (88.9)	157.5 (65.5)	158.6 (67.4)

Notes:
Unless otherwise noted, figures report cell means and standard errors in parentheses.
Figures are conditional on non-missing entries. Data refer to the 1994-95 school year.

[1] For children currently not in school, this refers to the grade level when they were last enrolled.
[2] PCE refers to annual per capita household expenditures. This is calculated as the annualized total household expenditures divided by total number of household members.
[3] Indicates the presence of a family business, not necessarily whether the child works for it.
[4] The physical facilities index is the sum of 10 indicators: whether main construction materials of school is concrete; school has electricity; has piped water supply; students have access to flush toilet (as opposed to latrine, open pit, or none); if no classes meet in classrooms separated by temporary partition; no multiple grade classrooms in school; no lack of classrooms; classes do not need to be moved/excused if it rains; if 100% of classrooms have useable blackboard; if there is a library.
[5] The resource index is out of 8 indicators: if school has a staff room; has file cabinets for records; has a telephone; has typewriter; if teachers have access to a computer; teachers are provided chalk; teachers provided pens, pencils, crayons; and are provided with paper.
[6] The National Elementary Assessment Test (NEAT) is a test administered to sixth grade pupils in all Philippine public and private elementary schools. This figure refers to the school-average NEAT score in the school nearest to the child's residence.

TABLE 2. Distribution of children by activity across IQ, PCE quantiles

IQ \ lnPCE	*Bottom Third*	*Middle*	*Upper Third*
Upper Third	Idle: 0.03 Work: 0 Schl & Work: 0.10 Schl: 0.87	Idle: 0.02 Work: 0 Schl & Work: 0.13 Schl: 0.85	Idle: 0.01 Work: 0 Schl & Work: 0.11 Schl: 0.88
Middle	Idle: 0.05 Work: 0 Schl & Work: 0.11 Schl: 0.84	Idle: 0.01 Work: 0.01 Schl & Work: 0.08 Schl: 0.90	Idle: 0 Work: 0 Schl & Work: 0.09 Schl: 0.91
Bottom Third	Idle: 0.11 Work: 0.04 Schl & Work: 0.12 Schl: 0.74	Idle: 0.07 Work: 0.02 Schl & Work: 0.11 Schl: 0.80	Idle: 0.07 Work: 0.01 Schl & Work: 0.08 Schl: 0.85

Source: CLHNS. Percentages add up to one within each cell.

TABLE 3. Determinants of Child Activity: Household Wealth and Child IQ

	(1)	(2)	(3)	(4)
	Parameters	Marginal Effects	Parameters	Marginal Effects
Idle				
LogPCE	-0.5595	-1.805	-0.3961	-1.028
	(0.0771)***	(0.227)***	(0.0801)***	(0.2092)***
LogIQ91			-2.2454	-5.919
			(0.3505)***	(0.9543)***
Constant	0.8831	3.437	8.1504	21.91
	(0.5083)*	(1.576)**	(1.3075)***	(3.350)***
Work Only				
LogPCE	-0.7808	-0.4287	-0.6306	-0.2862
	(0.1396)***	(0.0946)***	(0.1452)***	(0.0849)***
LogIQ91			-2.2259	-1.003
			(0.6836)***	(0.3525)***
Constant	0.7163	0.4792	8.0387	3.695
	(0.8532)	(0.4387)	(2.5151)***	(1.184)***
School & Work				
LogPCE	-0.0858	-0.5603	-0.0781	-0.5928
	(0.0518)*	(0.4865)	(0.0545)	(0.5136)
LogIQ91			-0.1962	-1.093
			(0.2860)	(2.699)
Constant	-1.4636	-14.17	-0.7411	-9.797
	(0.3832)***	(3.576)***	(1.0729)	(10.11)
No of observations	2192	2192	2192	2192
Log-Likelihood	-1187.59		-1153.91	

Notes: Standard errors are in parentheses. * indicates statistically significant at 10%; ** at 5%; *** at 1%. Marginal effects, evaluated at the mean, and associated standard errors are reported in percentage points. Baseline category is full-time schooling. Other regressors not reported in the table are dummy indicators for missing variables.

TABLE 4. Determinants of Child Activity: Household Wealth, IQ, Mother's Labor Supply, and School Quality
PANEL A. Parameter Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Idle	Work Only	School & Work	Idle	Work Only	School & Work	Idle	Work Only	School & Work	Idle	Work Only	School & Work
LogPCE	-0.2636	-0.5351	-0.0565	-0.2645	-0.5383	-0.0770	-0.2719	-0.5708	-0.1384	-0.2621	-0.5361	-0.1405
	(0.0886)***	(0.1716)***	(0.0615)	(0.0891)***	(0.1758)***	(0.0624)	(0.0903)***	(0.1784)***	(0.0636)**	(0.0911)***	(0.1829)***	(0.0636)**
LogIQ91	-1.8917	-1.8042	-0.1898	-1.9063	-1.7893	-0.2204	-1.9093	-1.7964	-0.2512	-1.8922	-1.6718	-0.2432
	(0.3696)***	(0.7153)**	(0.2944)	(0.3711)***	(0.7209)**	(0.2974)	(0.3711)***	(0.7227)**	(0.3029)	(0.3782)***	(0.7612)**	(0.3041)
female	-0.7038	-0.4786	0.2359	-1.2667	-19.7976	0.2699	-1.2707	-19.8267	0.2130	-1.3380	-20.4957	0.2109
	(0.2365)***	(0.4650)	(0.1415)*	(0.4495)***	(0.4930)***	(0.3420)	(0.4498)***	(0.4937)***	(0.3455)	(0.4525)***	(0.4981)***	(0.3462)
FatherED	-0.0935	-0.0929	-0.0125	-0.0954	-0.0893	-0.0098	-0.0944	-0.0857	-0.0026	-0.0885	-0.0553	-0.0046
	(0.0430)**	(0.0893)	(0.0244)	(0.0429)**	(0.0888)	(0.0247)	(0.0430)**	(0.0890)	(0.0249)	(0.0438)**	(0.0903)	(0.0253)
MotherED	-0.1029	-0.1130	0.0009	-0.1029	-0.1022	0.0020	-0.1024	-0.0995	0.0064	-0.0952	-0.1137	0.0042
	(0.0445)**	(0.0981)	(0.0250)	(0.0447)**	(0.1019)	(0.0253)	(0.0447)**	(0.1014)	(0.0257)	(0.0454)**	(0.1051)	(0.0259)
momwork				-0.0788	1.4354	1.4338	-0.1267	1.2654	0.9921	-0.1727	1.1056	0.9821
				(0.3054)	(1.0621)	(0.3153)***	(0.3162)	(1.0762)	(0.3267)***	(0.3192)	(1.0810)	(0.3274)***
momwrk*female				0.8139	19.5909	-0.0566	0.8212	19.6196	0.0195	0.8981	20.3910	0.0286
				(0.5310)	(0.0000)	(0.3764)	(0.5312)	(0.0000)	(0.3803)	(0.5344)*	(0.0000)	(0.3811)
FamBus							0.1303	0.4830	1.0375	0.1198	0.4531	1.0423
							(0.2394)	(0.4726)	(0.1602)***	(0.2420)	(0.4821)	(0.1606)***
LogDist										0.1211	0.5921	-0.0611
										(0.1695)	(0.3898)	(0.0992)
NEAT										0.0042	-0.0012	0.0001
										(0.0025)*	(0.0048)	(0.0013)
electricity										-0.6329	-0.6317	-0.0340
										(0.3036)**	(0.5913)	(0.2147)
Constant	7.3638	7.2749	-0.9130	7.4682	5.9400	-1.8392	7.5004	6.0547	-1.5890	6.3816	2.3054	-1.1949
	(1.3791)***	(2.6076)***	(1.1079)	(1.3978)***	(2.7873)**	(1.1467)	(1.4000)***	(2.7859)**	(1.1657)	(1.8230)***	(3.9167)	(1.3347)
No of Obs		2192			2192			2192			2192	
Log-Likelihood		-1133.73			-1104.73			-1081.80			-1071.54	

Notes: Standard errors are in parentheses. * indicates statistically significant at 10%; ** at 5%; *** at 1%. Baseline category is full-time schooling. Other regressors not reported in the table are dummy indicators for missing variables.

PANEL B. Marginal Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Idle	Work Only	School & Work	Idle	Work Only	School & Work	Idle	Work Only	School & Work	Idle	Work Only	School & Work
LogPCE	-0.559	-0.1873	-0.4503	-0.5603	-0.01016	-0.6063	-0.5713	-0.1058	-1.055	-0.5267	-5.542e-03	-1.073
	(0.1977)***	(0.0776)**	(0.5777)	(0.1993)***	(0.0047)**	(0.5361)	(0.2039)***	(4.823e-03)**	(0.5073)**	(0.1978)***	(2.820e-03)**	(0.5057)**
LogIQ91	-4.08	-0.6236	-1.274	-4.111	-0.0334	-1.491	-4.155	-0.03314	-1.632	-3.948	-0.01722	-1.584
	(0.0881)***	(0.3095)**	-2.767	(0.8898)***	(0.0183)*	(2.557)	(0.8986)***	(0.01823)*	(2.422)	(0.8785)***	(0.01106)	(2.425)
female	-1.592	-0.1746	2.407	-2.812	-0.3831	2.632	-2.832	-0.3794	1.992	-2.86	-0.2191	1.957
	(0.5189)***	(0.1701)	(1.323)*	(0.9767)***	(0.1664)**	(2.932)	(0.986)***	(0.1655)**	(2.757)	(0.9539)***	(0.1033)**	(2.755)
FatherED	-0.201	-0.03204	-0.0919	-0.2060	-1.670e-03	-0.06379	-0.2073	-1.596e-03	-1.859e-03	-0.186	-5.664e-04	-0.01963
	(0.0923)**	(0.03257)	(0.2298)	(0.09201)**	(1.794e-03)	(0.2123)	(0.09304)**	(1.773e-03)	(0.1995)	(0.09124)**	(9.954e-04)	(0.2015)
MotherED	-0.2245	-0.0397	0.03709	-0.2249	-1.938e-03	0.03914	-0.2267	-1.872e-03	0.07212	-0.2017	-1.198e-03	0.05127
	(0.09534)**	(0.03406)	(0.2353)	(0.09537)**	(1.959e-03)	(0.2173)	(0.09634)**	(1.932e-03)	(0.2054)	(0.09401)**	(1.098e-03)	(0.2065)
momwork				-0.4773	0.02517	12.37	-0.4760	0.02261	7.974	-0.5503	0.01095	7.88
				(0.6648)	(0.01831)	(2.508)***	(0.695)	(0.01851)	(2.508)***	(0.672)	(0.01071)	(2.507)***
momwork*female				1.779	0.3789	-0.697	1.796	0.3752	-0.0392	1.886	0.2179	0.03987
				(1.152)	(0.000)	(3.237)	(1.164)	(0.000)	(3.044)	(1.122)*	(0.000)	(3.041)
FamBus							0.08128	7.444e-03	8.288	0.05574	3.842e-03	8.306
							(0.5259)	(9.323e-03)	(1.228)***	(0.5095)	(5.317e-03)	(1.228)***
LogDist										0.267	6.363e-03	-0.5113
										(0.3568)	(4.509e-03)	(0.7906)
NEAT										8.842e-03	-1.418e-05	-3.561e-04
										(5.282e-03)*	(5.046e-05)	(0.01053)
electricity										-1.33	-6.579e-03	-0.1517
										(0.6499)**	(6.902e-03)	(1.712)
Constant	16.27	2.58	-10.62	16.68	0.1151	-17.45	16.83	0.1153	-14.23	13.70	0.02431	-10.76
	(3.144)***	(1.068)**	(10.39)	(3.208)***	(0.06829)*	(9.779)*	(3.242)***	(0.06808)*	(9.262)	(3.966)***	(0.04438)	(10.61)

Notes: * indicates statistically significant at 10%; ** at 5%; *** at 1%. Marginal effects (evaluated at the mean of variables) and associated standard errors reported in parentheses are in percentage points. Baseline category is full-time schooling. Other regressors not reported in the table are dummy indicators for missing variables.

TABLE 5. Changes in Predicted Probabilities for Child Activity

	Idle	Work	School & Work	School
LogPCE				
Min->Max	-0.10635	-0.0042	-0.13784	0.248392
-+1/2	-0.00528	-5.6E-05	-0.01073	0.016065
-+sd/2	-0.00735	-7.9E-05	-0.01492	0.022351
MargEfct	-0.00527	-5.5E-05	-0.01073	0.016053
LogIQ91				
Min->Max	-0.95014	-0.00206	0.066346	0.885847
-+1/2	-0.04458	-0.00019	-0.0152	0.059966
-+sd/2	-0.03795	-0.00016	-0.01343	0.051545
MargEfct	-0.03948	-0.00017	-0.01584	0.055494
female				
0->1	-0.0036	-0.64536	0.070096	0.578867
FatherED				
Min->Max	-0.03041	-9.6E-05	-0.00412	0.034629
-+1/2	-0.00186	-5.67E-06	-0.0002	0.002063
-+sd/2	-0.00857	-2.6E-05	-0.00089	0.009491
MargEfct	-0.00186	-5.66E-06	-0.0002	0.002062
MotherED				
Min->Max	-0.03374	-0.0002	0.009407	0.024534
-+1/2	-0.00202	-1.2E-05	0.000513	0.001517
-+sd/2	-0.00866	-5.2E-05	2.19E-03	0.006521
MargEfct	-0.00202	-1.2E-05	0.000513	0.001516

	Idle	Work	School & Work	School
momwork				
0->1	-0.00548	9.65E-05	0.070305	-0.06492
momwork*female				
0->1	-0.01583	0.990009	-0.08645	-0.88773
FamBus				
0->1	0.000366	3.81E-05	0.089448	-0.08985
LogDist				
Min->Max	0.022192	0.000815	-0.04909	0.026086
-+1/2	0.002672	6.46E-05	-0.00511	0.002377
-+sd/2	0.003462	8.45E-05	-0.00662	0.003078
MargEfct	0.00267	6.36E-05	-0.00511	0.002379
NEAT				
Min->Max	0.029744	-4.5E-05	-0.0013	-0.0284
-+1/2	8.84E-05	-1.42E-07	-3.56E-06	-8.5E-05
-+sd/2	0.006076	-9.72E-06	-0.00025	-0.00582
MargEfct	8.84E-05	-1.42E-07	-3.56E-06	-8.5E-05
electricity				
0->1	-0.01601	-7.9E-05	-0.00127	0.017356

Notes: Predicted probabilities are calculated from cols (10)-(12) of full multinomial logit model in Table 4. Changes in predicted probabilities is the difference in the predicted value as the independent variable changes while all others are held constant at their means. Independent variables go from its minimum to its maximum (Min→Max), from -0.5 units of its mean to +0.5 of the mean (-+1/2), ±0.5 standard deviation to the mean (-+sd/2), and from 0 to 1 in the case of dummy variables (0→1).

TABLE 6. Tests for Equality of Coefficients across Categories

	Idleness=Work Only	Work Only= School & Work	Idleness= School & Work
All coefficients (cols 10-12 in Table 4)	1577.75 [0.0]	3312.68 [0.0]	102.34 [0.0]
LogIQ91, LogPCE	2.04 [0.36]	8.74 [0.013]	15.41 [0.0]
FatherED, MotherED	1.69 [0.79]	2.63 [0.62]	14.32 [0.0]
Momwork, female*momwork	1357.5 [0.0]	2947.6 [0.0]	6.78 [0.034]
FamBus	0.61 [0.44]	1.12 [0.29]	10.68 [0.001]
LogDist, NEAT, electricity	48.8 [0.0]	47.77 [0.0]	4.85 [0.303]

Note: [p-values] below χ^2 test statistics.

TABLE 7. (Self-Reported) Primary Reason Why Not In School, By Child Labor

	Idleness	Work Only	Total
No Interest	35 (36.8%)	7 (33.3%)	36.21 %
Illness	19 (20.0%)	2 (9.5%)	18.10 %
Financial Problems	8 (8.4%)	5 (23.8%)	11.21 %
Gambling	9 (9.5%)	1 (4.8%)	8.62 %
Scared of teacher	6 (6.3%)	1 (4.8%)	6.03 %
Babysitting	3 (3.2%)	2 (9.5%)	4.31 %
Late for registration	4 (4.2%)	0	3.45 %
Works Fam Bus	1 (1.0%)	2 (9.5%)	2.59 %
Knows nobody	1 (1.0%)	0	0.86 %
School too far	1 (1.0%)	0	0.86 %
Did not respond	8 (8.4%)	1 (4.8%)	7.76 %