Is There a Child Labor Trap? Intergenerational Persistence of Child Labor in Brazil*

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I. Introduction

Child labor is a widespread phenomenon in the world, occurring predominantly in developing countries. Recently, politicians, activists, and academics alike have shown renewed concern about the persistence and impact of child labor. Most of the popular discussion has centered on the harmful effects of child labor and ways to curtail its incidence. In economics, much of the recent theoretical literature has focused attention on the fact that the decision to send children to work is most likely made not by the children themselves but by households who do so out of dire need.[1]

This realization has led to a new way of thinking about the effects of child labor and appropriate policy responses. If it is the head of the household that makes the child labor decision, it raises the possibility that there could be an intergenerational link in child labor. Some excellent recent theoretical work examines this link and identifies the potential for intergenerational child labor traps.[2] Despite this spate of theoretical work, however, there is a marked absence of empirical work on the topic.

This article examines the intergenerational persistence of child labor empirically by looking at household survey data from Brazil. Previous empirical work on child labor has focused primarily on isolating the determinants of child labor using survey data.[3] We take a different approach by asking, "Does the child labor status of parents affect the child labor incidence of their children?" We look at this question in two ways. Our working assumption is that financial need creates this generational link, but we also ask if there exists an intergenerational link over and above that which is transmitted through the production of income (perhaps through norms). We find strong evidence

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that this link exists and that it appears to persist even when income is held constant. Moreover, we find that children who did not work as child laborers command higher salaries later in life, which suggests that the potential human capital gains through apprenticeship as children are outweighed by the human capital gains children receive through schooling.

We begin our examination of the intergenerational persistence in child labor first by building an overlapping generations model of the household child labor decision and, second, by examining empirical evidence from Brazil. We keep our model simple and use it to motivate our empirical examination.

In our model, following K. Basu and P. H. Van, we assume that the child labor decision is made by the head of the household and that parents decide to send their child to work only if by doing so the child's contribution to the present consumption of the family outweighs the future consumption benefit the family would enjoy from keeping the child in school.[4] This is slightly different than Basu and Van's "luxury axiom," according to which parents send their children to work only if poverty forces them to do so.[5]

After constructing the model, we look for evidence of persistence in child labor by examining household survey data from Brazil. We exploit the fact that the data include information on the child labor of both parents and children in a family as well as information on the educational achievement of the grandparents. We find that people who start work as children end up with lower earnings as adults. Also, the likelihood of being child laborers increases the younger their parents were when they entered the labor force and the lower the educational attainment of their parents as well as their grandparents. All these findings are consistent with our own and other models of child labor and poverty persistence.

Perhaps most surprisingly, we find that this intergenerational persistence remains even when we control for household income and parental education. This result suggests that there is a link, beyond what is posited in the model, between the child labor of parents and the child labor of their children.

Together, the model and the empirical results paint a vivid picture of persistence in child labor between generations. The policy implications of these findings are potentially important; for example, there may be a critical level of resources needed to extract families from the child labor trap, after which no further resources are necessary. This is in contrast to many current policies that suggest the need to make provision for persistent support. As Basu and Van hypothesize, it is quite likely that the poor rely on child labor only to assure survival and, given a choice, would always opt for educating their children.[6] This article demonstrates that, if this is the case, the most appropriate policy response may be to concentrate on the condition of each family rather than focusing on individual children.

II. The Model

This section presents a simple model of intergenerational persistence of child labor incorporating the essential aspects of previous theoretical work. The recent theoretical literature on child labor and poverty traps incorporates a set of core assumptions: parents are altruistic toward their children, there is a trade-off between child labor and a child's human capital accumulation, the child's human capital accumulation is an increasing function of schooling, and the credit market is imperfect. Using some reasonable characterizations of parental preferences and a child's human capital accumulation, it is possible to generate a child labor trap model by incorporating these four main assumptions. The purpose of this model is to motivate and guide the empirical work that is the main contribution of this study. We do not test the model directly but, rather, look for evidence that supports the predictions of the model. This process works in both ways, however, and we allow our empirical investigation to extend beyond the predictions of the simple model to enlighten this link further and to inform future theoretical work.

We begin with a simple model wherein each family consists of one adult and one child. The adult values both current consumption and the educational attainment of the child. Educational attainment as a child determines the wage earnings when one is an adult. A child can go to school, work in the labor market, or both. The amount of time spent working detracts from the child's total educational attainment and thus diminishes the child's earnings once he or she reaches adulthood. Therefore, families with little education are more desperate for the contribution to current consumption the child can provide through work than are families with higher educational levels, and thus it is the families with lower educational levels that will send their children to work while families with higher educational levels will not.

Consider a household that consists of two agents in each period: an adult and a child. Each agent lives for two periods (child and adult); on reaching adulthood, each agent creates a child, making this a standard overlapping-generations model. All adults are identical, as are all children. There is no population growth, and we shall normalize the total population to the unit interval. We assume that the adult in each period makes the decision of whether to send the child to work (and thus forgo at least some of the child's education).[7] In addition, total human capital accumulation (from total education as a child) is the sole determinant of adult wage. We shall normalize the child wage to one and assume this to be the same as the wage for an adult worker with no education.

We shall first present the general model and, later, a specific model with an analytic solution. Here, however, we consider the household's child labor decision and describe situations in which a child labor trap can arise.[8]

In each period, the adult's utility is given by the function:

$$U_t = U(c_t, h_{t+1}), \tag{1}$$

where c_t is the period t consumption of the family and h_{t+1} is the human capital achievement of the child. Thus, the adult cares about the education of the child in and of itself.[9]

Adults are endowed with one unit of time in each period. As adults, all of the agent's time is spent working, and earnings are given by the production function

$$w_t^a = h_t, \tag{2}$$

where w_t^a is the adult's income and h_t is the stock of the adult's human capital.[10] The young are also endowed with one unit of time, which can be divided between schooling and work. By assumption, the child wage is normalized to one, so a child who spends all of his or her time working will earn $1. The child's production function is

$$w_t^c = 1 - e_t, \tag{3}$$

where w_t^c is the earnings of the child in period t, e_t is the time spent in school, and $e_t \in [0, 1]$. Total family earnings at time t are thus given by

$$W_t = w_t^a + w_t^c. \tag{4}$$

The budget constraint for the family is

$$c_t \leq W_t, \tag{5}$$

which will bind by nonsatiation as long as the marginal utility derived from increased consumption is always greater than zero.

We assume that there exists a technology that converts education as a child into adult human capital, or

$$h_{t+1} = f(e_t), \tag{6}$$

where $f(0) = 1$, $f(1) = \bar{h} > 1$, and $f'(e_t) \geq 0$ for all $e_t \in [0, 1]$.

We can substitute the constraints into the objective function of equation (1) and derive the adult's problem:

$$\max_{\{e_t\}} U[h_t + 1 - e_t, f(e_t)]. \tag{7}$$

Let e^* be the solution to the adult's problem. We can now express the optimal education level of the child as a function of the adult's human capital:

$$e^* = g(h_t), \tag{8}$$

where $g(.)$ depends on the functional forms of $U(.)$ and $f(.)$ The law of motion is then

$$h_{t+1} = f[g(h_t)] \equiv \phi(h_t). \tag{9}$$

Depending on the functional forms of $f(.)$ and $g(.)$, the $\phi(.)$ function can take on many different shapes. One such possible shape is of the type illustrated in figure 1, where $f'(.)$ and $g'(.)$ are positive. This is a case in which a child labor trap can arise. Here there are multiple steady state equilibria; two stable and one unstable. One stable equilibrium exists at $h_t = 1$, and the other at $h_t = \bar{h}$. The unstable equilibrium is at $h_t = h^*$. In fact, h^* is a critical value of human capital attainment, for when the adult's human capital is below

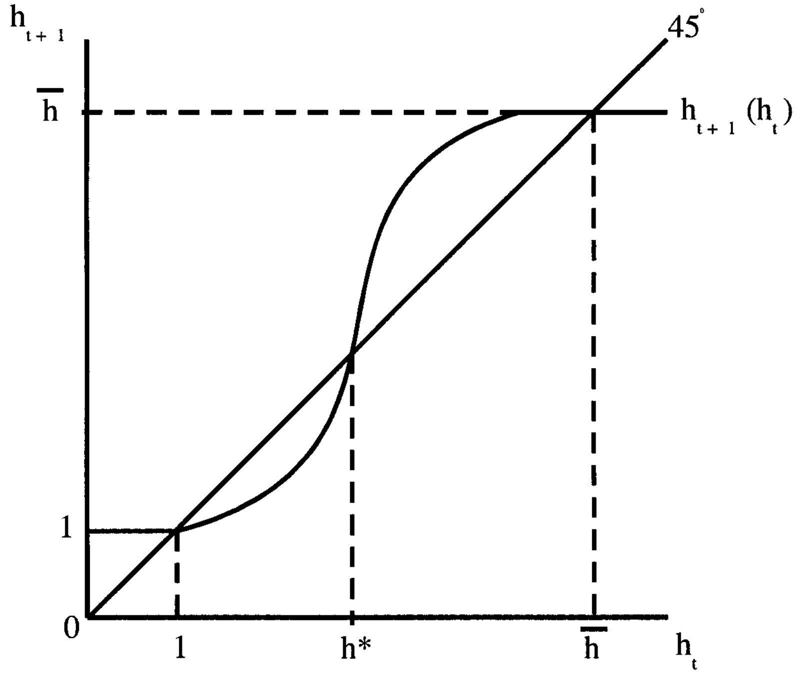

FIG. 1.—The h_{t+1} function

h^*, the child will end up with even less human capital until the family reaches the steady state of $h_t = 1$, where the children do nothing but work. Alternatively, if the adult's human capital is above h^*, the child will end up with more human capital than the adult, and the family will eventually reach the steady state of $h_t = \bar{h}$, where the children do no work and attend school full-time.

It is important to note that this model implicitly assumes that there is no access to capital markets for these families (i.e., they cannot borrow against the future earnings of the children) and that there is no uncertainty in this economy. Efficient credit markets can alleviate the tension in this model between current consumption and children's human capital and, in general, can have important mitigating effects on child labor, as shown by P. Ranjan.[11] Again, our attempt is to describe as simple a model as possible, but capital markets that are available to the poor of the developing world are generally considered, at best, imperfect, and uncertainty would not alter the main results of the model.

As a concrete example that gives rise to the type of shape of the $\phi(.)$ function illustrated above, a specific case is given below. Consider a utility function of the Cobb-Douglas type:

$$U(c_t,\ h_{t+1}) = c_t^{\alpha} h_{t+1}^{1-\alpha},\ \alpha \in (0,\ 1), \tag{1'}$$

where equations (2), (3), (4), and (5) are all the same as given above. The parameter in this function represents the relative weight the family places on current consumption and the child's human capital attainment. Now suppose that the returns to education are "lumpy." For example, there may be discrete jumps in the returns to education when a person reaches the stages of literacy, primary education, secondary school diploma, and so on.[12] For simplicity, we assume a polar case in which the returns to education are zero unless the child spends all of his or her time in school (perhaps until the end of secondary school). In reality, there are likely to be many intermediate levels, but as long as discrete jumps exist, the analysis will be essentially the same, although intermediate equilibria could arise. In this case, we assume that possessing a secondary school diploma allows an individual to command a much higher wage than a person who has completed virtually as much schooling but who does not possess a diploma. We can capture this idea with a new technology that converts education into adult human capital in the following way:

$$\begin{cases} \Theta, & \text{if } e_t = 1 \\ 1, & \text{if } e_t < 1 \end{cases}, \tag{6$'$}$$

where $e_t \in [0, 1]$, and $\Theta > 1$. The value of Θ can be interpreted as returns to education or simply as the educated adult wage rate. This illustrates the polar case in which an adult who does not have a secondary school diploma commands a wage of one, the same as a child laborer. This polar case is considered to simplify the analysis. Note that in this case, no one will select a level of education between zero and one because education is costly.

We can solve this problem analytically, as the adult's decision is now a binary one: send the child to school or to work. The adult will send the child to school ($e_t = 1$) if and only if

$$U_t^{e_t=1} \geq U_t^{e_t=0}. \tag{10}$$

After plugging in the budget constraint (and noting that nonsatiation holds with this utility function), this decision rule becomes

$$U_t^{e_t=1} = (h_t)^{\alpha}(\Theta)^{1-\alpha} \geq (h_t + 1)^{\alpha}(1)^{1-\alpha} = U_t^{e_t=0}, \tag{11}$$

which reduces to

$$h_t \geq [\Theta^{(1-\alpha/\alpha)} - 1]^{-1} \equiv h^*. \tag{12}$$

So equation (12) defines the critical value of h^*, at which point adults who have human capital h^* and above will send their children to school full-time, and those who do not will send their children to work full-time. There are, therefore, two steady state equilibria in this model, at full education and at no education. This is illustrated in figure 2.

For a wide range of parameterizations, $h^* \in [1, \Theta]$., then $h^* = 1.33\bar{3}$. It is also interesting to note that h^* is increasing in α and decreasing in Θ. Thus, the more weight the adult places on current consumption as opposed to the child's human capital achievement, the more likely the adult is to make

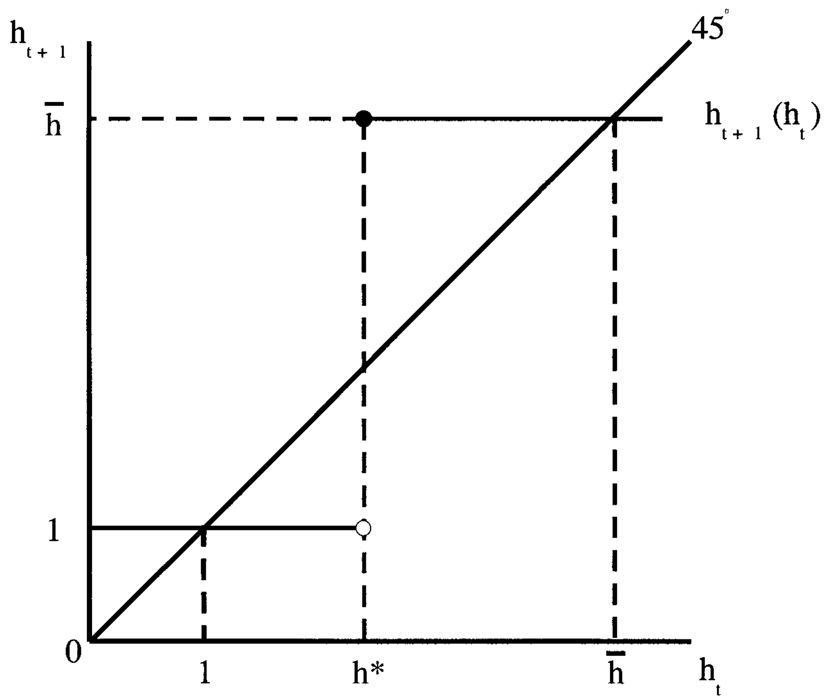

FIG. 2.—The h_{t+1} function with discrete returns to education

the choice of zero education. In addition, the higher the returns to education, the more likely the adult is to make the choice of full education.

While this specific model is a polar version of the returns to education or the child labor choice, we believe that it illustrates well the fundamental intergenerational link between the child labor of the parents and their offspring. This is the link that we explore empirically in Section III, and this model serves as a guide for our empirical investigation.

III. Empirical Evidence from Brazil

A. The Data

The data used in this study come from the 1996 Brazilian Household Surveys, called Pesquisa Nacional por Amostragem a Domicilio (PNAD), which are conducted by Instituto Brasileiro de Geografia e Estatística (IBGE), the Brazilian census bureau. It is an annual labor force survey much like the Current Population Survey in the United States. Covering all urban areas and the majority of rural areas in Brazil (with the exception of the rural areas of the Amazon region), the sample is based on a three-stage sampling design. With the exception of the first stage, the sampling scheme is self-weighted, and the sampling varies across regions and over time. The 1996 PNAD encompasses approximately 85,000 households.

The sample selection of this study consists of individuals between 10 and 14 years of age who are considered a son, daughter, or other relative in the family unit.[13] There are 36,975 observations for children in this age cohort. Each observation consists of information on the child characteristics, his or her parent characteristics, and his or her family characteristics. Since we are concerned primarily with the impact of the parents' child labor status on the child labor status of the children, we use a sample of observations with complete information on the father's and the mother's characteristics. Given this criterion, families with single heads of households are excluded from the analysis.[14] Finally, all observations for which the age difference between the head of the family or spouse and the oldest child is 14 years or less are excluded as well. Excluding the above observations reduced our sample by 8,170 to 28,805, or 22%.

The child labor variable for the children is constructed as follows: a child is considered as working if he or she worked on the labor market any strictly positive hours per week.[15] To check the robustness of our results, we estimated the same models using an alternate definition of child labor, namely, if he or she worked 20 hours or more on the labor market per week. The results using this alternate definition are qualitatively the same and are not presented here but are available on request.

The child labor variable for the parents is defined as follows. The PNAD survey asks each individual the age at which he or she started working. A parent who responded that they began working in the labor market at age 14 or younger is considered to have been a child laborer. We also used an alternate definition for which we considered an adult to have been a child laborer if they had entered the labor force at age 10 or younger to check the robustness of the results and to account for any generational differences in child labor norms. As with the child's child labor variables, the results for the estimation with this alternate definition are qualitatively the same and are available on request.

For each child, we also obtained his or her school attendance status, gender, and region of residence. Similarly, we constructed years of schooling, age, and employment status of the parents. The basic statistics of all the variables used in this analysis are presented in table A1.[16]

Table 1 presents the proportions of child labor and an adult's child labor status in 1996 for the baseline definitions of child labor for the children and parents. In table 1, of all 10–14-year-old children in the sample, 13.9% worked in the labor market. For these children, 70.6% of their fathers were child laborers, and 37.2% of their mothers started working at age 14 or younger. More important, of all children belonging to a family in which the father was a child laborer, 17.3% are child laborers. On the other hand, of all children coming from a family in which the father was not a child laborer, only 5.9% are child laborers. Similarly, of all children who belong to a family in which the mother was a child laborer, 24.3% are child laborers. Of all children coming from a family in which the mother was not a child laborer, around 7.8% are child laborers. Note that 67.8% of children who are not child laborers have

TABLE 1

Unconditional Probabilities: Child Working Strictly Positive Hours—Parent Began Working at Age 14 or Younger

Son or Daughter Is a Child Laborer	Father Was a Child Laborer		Mother Was a Child Laborer		
	No	Yes	No	Yes	Total
No:					
Number	7,991	16,833	16,708	8,116	24,824
Row (%)	32.19	67.81	67.31	32.69	100
Column (%)	94.1	82.72	92.19	75.72	86.07
Yes:					
Number	501	3,517	1,416	2,602	4,018
Row (%)	12.47	87.53	35.24	64.76	100
Column (%)	5.9	17.28	7.81	24.28	13.93
Total:					
Number	8,492	20,350	18,124	10,718	28,842
Row (%)	29.44	70.56	62.84	37.16	100
Column (%)	100	100	100	100	100

fathers who were (and 32.7% have mothers who were). This reflects the fact that the child labor market participation rates in Brazil have been falling through time since at least 1950.

Tables 2 and 3 present similar figures for daughters only and sons only, respectively. For female children ages 10–14 in our sample, 8.7% are child laborers, while that figure is 19.1% for male children. Table 2 shows that, in terms of unconditional probabilities, a daughter whose father was a child laborer is approximately eight times more likely to be a child laborer as compared with a daughter whose father was not a child laborer and more than twice as likely to have a mother who was a child laborer. For sons, as shown in table 3, these figures are approximately three and four times, respectively. Although these figures are unconditional probabilities, they suggest the existence of intergenerational persistence in child labor in Brazil.

B. Empirical Models of Intergenerational Persistence of Child Labor

To test the intergenerational effect of child labor, we estimate two different models. The first is a probit model of the child labor indicator variable on parents' child labor status and a vector of other controls. The second is a Cox proportional hazard model of the number of years between birth and the age at which the child entered the labor force on the parent's child labor indicator variable plus a set of control variables. The empirical literature on child labor emphasizes the fact that the child labor decision is in fact a joint child labor and school attendance decision.[17] To account for this decision structure, we additionally estimate three different models, each of which depends on the assumptions of the decision-making process. We estimated a sequential probit model, following Christian Grootaert and Harry A. Patrinos, in which the school versus work decision is assumed to be sequential.[18] We also estimated

TABLE 2

Unconditional Probabilities, Daughters Only: Daughter Working Strictly Positive Hours—Parent Began Working at Age 14 or Younger

Daughter Is a Child Laborer	Father Was A Child Laborer		Mother Was a Child Laborer		
	No	Yes	No	Yes	Total
No:					
Number	4,064	8,908	8,538	4,434	12,972
Row (%)	31.33	68.67	65.82	34.18	100
Column (%)	96.51	89.18	96.06	83.47	91.35
Yes:					
Number	147	1,081	350	878	1,228
Row (%)	11.97	88.03	28.5	71.5	100
Column (%)	3.49	10.82	3.94	16.53	8.65
Total:					
Number	4,211	9,989	8,888	5,312	14,200
Row (%)	29.65	70.35	62.59	37.41	100
Column (%)	100	100	100	100	100

a multinomial logit model and a bivariate probit model that assume that the decision is made on all of the options simultaneously. Given that we are primarily concerned with the persistence of child labor and that the main results hold for all models, we will present the first two models only. We believe that the two models presented below are sufficient evidence to support our main hypothesis. However, the results for the other three models support our findings from the probit and Cox models and are available on request.

Probit model. To estimate the effect of parental child labor on the incidence of work among youths ages 10–14, we first estimate a standard

TABLE 3

Unconditional Probabilities, Sons Only: Son Working Strictly Positive Hours—Parent Began Working at Age 14 or Younger

Son Is a Child Laborer	Father Was a Child Laborer		Mother Was a Child Laborer		
	No	Yes	No	Yes	Total
No:					
Number	3,927	7,925	8,170	3,682	11,852
Row (%)	33.13	66.87	68.93	31.07	100
Column (%)	91.73	76.49	88.46	68.11	80.95
Yes:					
Number	354	2,436	1,066	1,724	2,790
Row (%)	12.69	87.31	38.21	61.79	100
Column (%)	8.27	23.51	11.54	31.89	19.05
Total:					
Number	4,281	10,361	9,236	5,406	14,642
Row (%)	29.24	70.76	63.08	36.92	100
Column (%)	100	100	100	100	100

TABLE 4

Child Labor Persistence: Probit on Child Labor Indicator Variable

Independent Variables	Coefficient (1)	SE (2)	Coefficient (3)	SE (4)	Coefficient (5)	SE (6)
Child laborer father	.333**	.029	.259**	.030	.251**	.039
Child laborer mother	.407**	.027	.319**	.028	.320**	.036
Father's schooling (years)	…	…	−.028**	.004	−.025**	.005
Mother's schooling (years)	…	…	−.030**	.004	−.033**	.005
Age of the child	.208**	.008	.211**	.008	.214**	.010
Paternal grandfather's schooling (years)	…	…	…	…	.000	.009
Paternal grandmother's schooling (years)	…	…	…	…	−.008	.009
Maternal grandfather's schooling (years)	…	…	…	…	−.001	.008
Maternal grandmother's schooling (years)	…	…	…	…	.002	.009
Female child	−.587**	.032	−.593**	.032	−.587**	.042
Urban	−.842**	.023	−.730**	.024	−.736**	.030
Father not in the labor market	−.172**	.045	−.236**	.046	−.251**	.062
Mother not in the labor market	−.270**	.027	−.361**	.029	−.361**	.036
Father's age	.008**	.002	.005**	.002	.002	.002
Mother's age	.003	.002	.000	.002	.003	.003
No. of boys ages 0–5	.059	.022	.033	.022	.001	.029
No. of boys ages 6–9	.118**	.020	.087**	.020	.063*	.027
No. of boys ages 10–14	.085**	.018	.059**	.018	.040	.022
No. of boys ages 15–17	.036	.020	.012	.020	.038	.026
No. of girls ages 0–5	.126**	.021	.096**	.021	.128**	.027
No. of girls ages 6–9	.122**	.020	.092**	.020	.109**	.025
No. of girls ages 10–14	.078**	.018	.049**	.018	.028	.023
No. of girls ages 15–17	−.022	.023	−.040	.023	.043	.029
Constant	−3.871**	.119	−3.255**	.124	−3.245**	.159
No. of observations	28,805	28,665	17,687			
χ^2 (n)	4,018.73 (17)	4,094.19 (19)	2,542.85 (23)			
Psuedo R^2	.230	.242	.248			

Note.—White's heteroskedastic consistent errors used in all regressions.
* Statistically significant at the 5% level.
** Statistically significant at the 1% level.

probit model.[19] The dependent variable is an indicator that equals one if the child usually works any strictly positive hours in the labor market. This is regressed on indicator variables that equal one if the child's mother and father were child laborers (began working at age 14 or younger). Also included are the age of the child, the age of the parents, the number of brothers and sisters ages 0–5, 6–9, 10–14, and 15–17, and indicators for if the child is female, lives in an urban area, has a father who is not in the labor market, and has a mother who is not in the labor market.[20] The results are shown in the first column of table 4.[21]

We find that parental child labor has a strong and positive effect on the probability that a child is in the labor force. Moreover, a female child and children in urban areas are less likely to work in the labor market. Also, the greater the number of siblings ages 5–14, the more likely the child is to work. Children are also less likely to work if either parent is not in the labor market.[22]

If the child labor trap explanation outlined in the model is the only determinant of the intergenerational persistence of child labor, then the parental child labor effect should vanish when one controls for family wealth or any appropriate proxy for it. One such potential proxy is the education of the parents.

Table 4, column 3, shows the results of the regression when the parents' years of schooling are added as dependent variables. As expected, the years of schooling of the parents have a strongly negative and significant effect on the child's probability of working. These results indicate that children are more likely to be a laborer if their parents were child laborers and less likely the more educated their parents are. Note, however, that the effect of parental child labor remains positive and statistically significant.

To evaluate the impact of the grandparents' education on the child labor status of the grandson or granddaughter and, possibly, to enhance the proxy for family permanent income, we also estimate a probit model that includes the years of schooling of grandparents as explanatory variables.[23] Table 4, column 5, shows the coefficients from the complete set of regressors. When we include the parents' education variables, the years of schooling of grandparents become insignificant. These results suggest that there is no direct link between grandparents' education and the child labor status of the grandchild. Although not reported, we estimated a probit including grandparents' years of schooling but excluding the parents' years of schooling variables. In this case, the grandparents schooling variables became significant. Thus, the schooling effect appears to operate through the education of the parents only. Note that the coefficients on the number of brothers ages 10–14 and on the number of sisters ages 10–14 are no longer significant, which could result from a correlation between the grandparents, education, and the family size.

Adding income of the family in our probit specification is likely to suffer from an endogeneity problem, but considering it as an explanatory variable is useful, for it can help determine if education of the parents is just a proxy for permanent family income. The income of the family minus the income from all children is included in the regressions in table 5. The first specification includes both the family-income variable as well as the parents' education variable. The results of this regression are given in the first column of table 5. In this case, the coefficients on both parents' child labor indicator variables are positive and significant, and the coefficients on the parents' education variables are negative and significant. The coefficient on the family-income variable is not significant, however. In the second specification, shown in table 1, column 3, the schooling of the parents is not included. Here, the coefficients on the parents' child labor indicator variables are still positive and significant, but now the coefficient on the family-income variable is negative and significant.

These results are unexpected and quite striking, for it appears that there is an effect of parental child labor over and above the effect on family income and parental education. These results are not predicted by our simple model and suggest that the effects of parental child labor may be more complex than

TABLE 5

Child Labor Persistence: Probit on Child Labor Indicator Variable, including Family Income as Explanatory Variable

Independent Variables	Coefficient (1)	SE (2)	Coefficient (3)	SE (4)
Child laborer father	.258**	.031	.310**	.030
Child laborer mother	.319**	.028	.369**	.028
Father's schooling (years)	−.026**	.004	…	…
Mother's schooling (years)	−.028**	.004	…	…
Age of the child	.212**	.008	.211**	.008
Female child	−.583**	.033	−.578**	.033
Urban	−.718**	.024	−.783**	.024
Father not in the labor market	−.244**	.046	−.230**	.046
Mother not in the labor market	−.363**	.029	−.314**	.028
Father's age	.005**	.002	.008**	.002
Mother's age	.001	.002	.003	.002
No. of boys ages 0–5	.037	.022	.052*	.022
No. of boys ages 6–9	.081**	.021	.101**	.021
No. of boys ages 10–14	.058**	.018	.073**	.018
No. of boys ages 15–17	.011	.021	.032	.021
No. of girls ages 0–5	.095**	.022	.115**	.022
No. of girls ages 6–9	.095**	.020	.113**	.020
No. of girls ages 10–14	.047**	.018	.065**	.018
No. of girls ages 15–17	−.030	.024	−.015	.023
Family income minus child income	−.00002	.00002	−.00012**	.00002
Constant	−3.311**	.126	−3.797**	.121
No. of observations	27,791		27,926	
χ^2 (n)	3,935.88 (20)		3,837.11 (18)	
Psuedo R^2	.2384		.2308	

Note.—White's heteroskedastic consistent errors used in all regressions.
* Statistically significant at the 5% level.
** Statistically significant at the 1% level.

the simple human capital relationship posited in our model. This suggests that future research is needed to shed more light on this aspect of child labor. For example, human capital accumulation may be determined not only by the amount of education but also by the quality of education, the level of education of siblings, the household environment, and so on.

Nonetheless, the results suggest that there is indeed a "family wealth effect" on child labor. To illustrate the interaction between parental child labor status and their educational achievement, figure 3 presents the difference in the probability of working in the labor market for a 12-year-old child coming from a family with parents who were child laborers as compared with a 12-

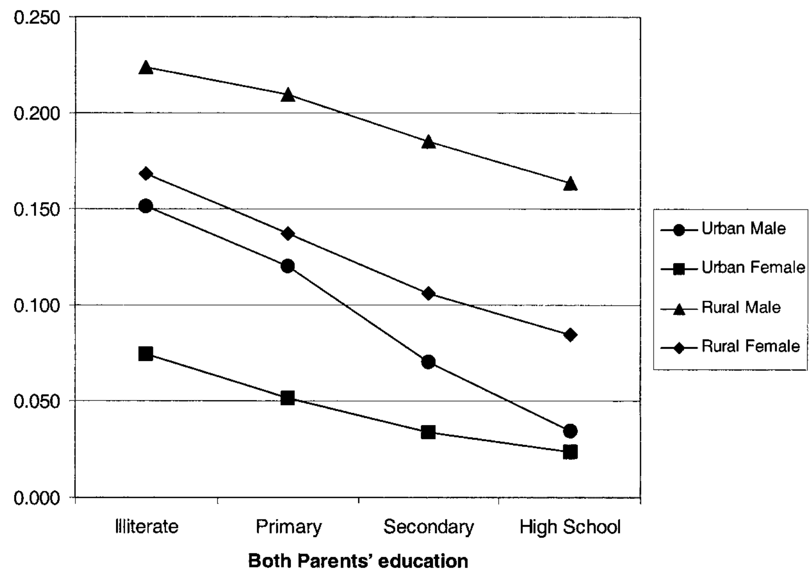

FIG. 3.—Effect of education on the intergenerational persistence of child labor

year-old child coming from a family where parents were not child laborers. It is assumed that both parents have the same level of education, are both in the labor market, are 40 years old, and have only one child. The probability differences are constructed for sons and daughters in rural and urban areas separately and use the coefficients from table 4, column 1. Notice first that, for any level of parental education, a child who belongs to a family with parents who were child laborers is more likely to be a child laborer. Second, this difference decreases as the education level of the parents increases. This is exactly what we would expect from our child-labor trap hypothesis.

The Cox proportional hazard model. An alternate way to evaluate the intergenerational persistence of child labor is to estimate a Cox proportional hazard model of the number of years between birth and the age at which the child entered the labor market.[24] This model accounts for the fact that we have censored observations in our data set. These censored observations come from the fact that households are sampled once, and at that time children are asked if they are active in the labor market. Consider an 11-year-old child who answers “no.” He or she is considered not to be a child laborer in our estimation, *even though* he or she may enter the labor market the next day. By lumping all children ages 10–14 who answer “no” together in one category, we are not accounting for the fact that many of the children will enter the labor force before the age of 14, which we do not observe. The Cox hazard model allows us to account for exactly this problem.

To estimate a hazard model, it is necessary to create the duration variable. In our case, this variable is uncensored for those children who started working at age 14 or younger and right-censored for those children who have not yet

TABLE 6

Survival Function: Number of Years between Birth and Entering Labor Market

Time	Beginning Total	Fail	Net Lost	Survival Function	SE
4	28,847	5	0	.9998	.0001
5	28,842	41	0	.9984	.0002
6	28,801	105	0	.9948	.0004
7	28,696	260	0	.9858	.0007
8	28,436	594	0	.9652	.0011
9	27,842	754	0	.939	.0014
10	27,088	1,153	5,329	.8991	.0018
11	20,606	472	5,009	.8785	.002
12	15,125	545	4,823	.8468	.0023
13	9,757	385	4,713	.8134	.0028
14	4,659	228	4,431	.7736	.0037

started working. We obtain this variable by assigning the age at which the child started working for those active children and by assigning the age of the child for those children who are not in the labor market.[25] Our explanatory variables in this model are the same as in the probit model from the previous section, except that we exclude the child's age.

The Cox hazard model answers a slightly different question than the probit model above. Whereas the probit model concerns the probability that children will be child laborers, the Cox model concerns the likelihood that children will enter the labor force earlier in life. We expect that, ceteris paribus, the parents' having been child laborers increases the likelihood that the child will enter the labor force earlier in life. We also expect that the more years of schooling the parents have, the less likely it is the child will enter the labor force earlier in life.

The survival function for the model is shown in table 6, and the results of this model are shown in table 7. In table 7, as expected, the child labor incidence of both parents increases the probability of the child entering the labor force at a younger age—and these results hold even when we control for parental schooling. Again, the greater the level of both parents' schooling, the greater the decreased probability of the child's entering the labor force at a younger age. Also, girls are less likely to enter the labor force earlier (outside the home) than are boys, and urban children are less likely to enter the labor force earlier than are rural children. Once more, the grandparents' years of schooling do not affect the probability of the child's entrance into the labor force earlier, as revealed by the last two columns of table 7. The results from this Cox proportional hazard model are qualitatively similar to the results of the probit estimation given in table 4.

C. The Cost of Child Labor

So far, we have shown strong evidence of intergenerational persistence of child labor in Brazil. However, to explain why we should be concerned with

TABLE 7

Child Labor Persistence: Cox Proportional Hazard Model on Number of Years between Birth and Entering Labor Market

Independent Variables	Hazard Ratio	SE	Hazard Ratio	SE	Hazard Ratio	SE
Child laborer father	1.883**	.090	1.656**	.081	1.636**	.105
Child laborer mother	2.063**	.084	1.806**	.076	1.827**	.097
Father’s schooling (years)	…	…	.958**	.006	.966**	.008
Mother’s schooling (years)	…	…	.943**	.006	.942**	.008
Paternal grandfather’s schooling (years)	…	…	…	…	.996	.014
Paternal grandmother’s schooling (years)	…	…	…	…	.982	.014
Maternal grandfather’s schooling (years)	…	…	…	…	.997	.013
Maternal grandmother’s schooling (years)	…	…	…	…	1.001	.014
Female child	.419**	.019	.420**	.019	.426**	.024
Urban	.295**	.009	.358**	.012	.347**	.014
Father not in the labor market	.927	.061	.852*	.057	.782**	.073
Mother not in the labor market	.744**	.031	.660**	.029	.658**	.036
Father’s age	1.009**	.002	1.004	.002	1.002	.003
Mother’s age	1.006*	.003	1.002	.003	1.006	.004
No. of boys ages 0–5	1.069*	.031	1.027	.030	.986	.039
No. of boys ages 6–9	1.146**	.033	1.094**	.031	1.037	.038
No. of boys ages 10–14	1.138**	.027	1.102**	.026	1.090**	.032
No. of boys ages 15–17	1.045	.029	1.008	.028	1.043	.037
No. of girls ages 0–5	1.177**	.034	1.130**	.032	1.200**	.044
No. of girls ages 6–9	1.163**	.031	1.1088**	.0292	1.151**	.039
No. of girls ages 10–14	1.115**	.027	1.0631*	.0260	1.040*	.033
No. of girls ages 15–17	.973	.031	.9447	.0304	.927	.038
No. of observations		28,807		28,667		17,687
χ^2 (n)		4,987.89 (16)		5,215.85 (18)		3,273.35 (22)

Note.—White’s heteroskedastic consistent errors used in all regressions.
* Statistically significant at the 5% level.
** Statistically significant at the 1% level.

the incidence of child labor, it is important to look at the economic consequences of child labor in a person's life. One main negative effect of child labor is the potential for child labor to hamper the ability of the adult to generate higher earnings.

To assess the impact of having been a child laborer on current earnings, we estimate both a simple ordinary least squares regression and a Heckman selection model for both mothers and fathers in the sample. In these specifications, we regress the log of current earnings on age and age-squared, age that they started work and its square, the grandfather's years of schooling, the grandmother's years of schooling, and a race indicator variable. In addition, in separate specifications, we add the individual's years of schooling. For the selection-bias corrected estimations, we add the number of sons and daughters ages 0–9 years old in the first-stage regression. The results are given in table 8.

For both fathers and mothers, the coefficient on the age at which they started work is positive and significant in all specifications. In the specification that excludes the years of schooling variables, the age-started work coefficients can be interpreted as the forgone earnings of an individual entering the labor market 1 year earlier. Moreover, child labor has a negative impact on current earnings even when we control for education and other variables. This means that there are negative aspects to having been a child laborer over and above that of losing out on education. Thus, there do not appear to be positive effects on adult earnings for gaining work experience as a child laborer. The squared term is negative and significant, meaning that the marginal negative impact of child labor for adults lessens the later the individual enters the labor force.

IV. Conclusion

This article presents an overlapping-generations model of intergenerational child labor persistence and finds strong evidence of such a link in Brazil. The results suggest that there is a significant relationship between a parent's child labor incidence and years of schooling and those of their children. We find that children are more likely to be child laborers if their parents were as well. In addition, we find that children are less likely to be child laborers the more educated their parents are. Moreover, the educational attainment of grandparents does not directly affect the child's labor status, but there seems to be an indirect impact that is transmitted through the parents' education. These results also hold when we control for family income. Additionally, earnings of an adult are lower, ceteris paribus, the earlier the individual enters the labor market. Together, these results paint a striking picture of the intergenerational persistence and harmful effects of child labor within families.

Surprisingly, there appears to be an intergenerational effect of child labor over and above that which is transmitted through household income and parental education. This result suggests that richer models are needed with a more sophisticated view of the household child labor choice that accounts for this aspect of persistence. On the one hand, if this result comes from some unobservable human capital characteristic that is captured by the parents'

TABLE 8

EFFECT OF CHILD LABOR ON LOG OF ADULT EARNINGS OF FATHERS AND MOTHERS: OLS AND HECKMAN MODEL ESTIMATES

INDEPENDENT VARIABLES	OLS				Heckman			
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Father:								
Age started work	.06132**	.00869	.05130**	.00766	.06018**	.00874	.05101**	.00768
Age started work-squared	−.00070**	.00031	−.00156**	.00028	−.00066**	.00032	−.00155**	.00028
Years of schooling	…	…	.11969**	.00166	…	…	.11944**	.00173
Father's schooling (years)	.07389**	.00317	.01954**	.00290	.07329**	.00320	.01949**	.00290
Mother's schooling (years)	.07557**	.00351	.02178**	.00318	.07557**	.00352	.02189**	.00319
Age	.07983**	.00601	.05777**	.00530	.07634**	.00621	.05694**	.00553
Age-squared	−.00094**	.00006	−.00064**	.00006	−.00090**	.00007	−.00063**	.00006
Nonwhite	−.44442**	.01352	−.27841**	.01214	−.44054**	.01367	−.27771**	.01221
Constant	3.52783**	.15250	3.65264**	.13444	3.62497**	.15853	3.67701**	.14208
No. of observations	17,950		17,925		19,571		19,543	
R^2	.3133		.468					
Lambda					−.182	.075	−.047	.088
χ^2 (n)					7,342.63 (7)		13,041.52 (8)	

Mother:								
Age started work	.09744**	.00590	.03040**	.00548	.07096**	.00651	.01697**	.00590
Age started work-squared	−.00208**	.00014	−.00073**	.00013	−.00163**	.00016	−.00053**	.00014
Years of schooling	…	…	.10580**	.00224	…	…	.08790**	.00281
Father's schooling (years)	.07091**	.00394	.03240**	.00362	.06404**	.00422	.03293**	.00386
Mother's schooling (years)	.06762**	.00424	.01961**	.00394	.05807**	.00457	.01913**	.00420
Age	.14297**	.01366	.06467**	.01239	.10366**	.01434	.03954**	.01290
Age-squared	−.00165**	.00017	−.00070**	.00015	−.00114**	.00017	−.00037**	.00016
Nonwhite	−.38613**	.01926	−.27747**	.01745	−.37555**	.02026	−.28780**	.01837
Constant	1.25984**	.27920	2.92562**	.25350	2.57553**	.30262	3.89807	.27312
No. of observations	8,943		8,893		13,151		13,093	
R^2	.3047		.4444					
Lambda					−.547	.038	−.496	.041
χ^2 (n)					2,019.71 (7)		2,818.71 (8)	

NOTE.—White's heteroskedastic consistent errors used in all regressions.
* Statistically significant at the 5% level.
** Statistically significant at the 1% level.

child labor variables (e.g., school quality), then our finding is essentially capturing the intergenerational poverty persistence, and it is thus consistent with our child labor trap model. On the other hand, if it comes from a difference in the preferences of households in which parents were child laborers, or if different social norms were associated with child labor experience, then the current theoretical child labor literature is not adequate to explain child labor in Brazil. Further research is needed to uncover this aspect of the persistence in child labor along with richer models.

Nonetheless, these results suggest that it might be better to treat households as a whole when it comes to designing policies aimed at reducing the incidence of child labor. These policies are important because in this article we also show that child labor has harmful effects on individuals' earnings abilities as adults. The negative effect of the loss of educational attainment is greater than the positive effect of gaining experience as a child laborer.

This article has shown that the overall harmful effects of child labor extend well beyond the childhood years. The same child laborer as an adult does worse than a person who was not a child laborer, and that child laborer is much more likely to have to resort to sending their own children to work. Thus the cycle continues. It is important to break this cycle within each household in order to achieve a lasting, long-run reduction of child labor in a society. Policies that are able to break this cycle family by family are potentially the most effective instruments reducing the incidence of child labor.[26] This type of policy might, for example, involve a one-time transfer of a critical level of resources to a family rather than continual general support of children's education.

Appendix

TABLE A1

Sample Statistics of the Variables Used in the Empirical Analysis

Variables	Observations	Mean	SD	Minimum	Maximum
Children's variables:					
Age	28,847	12.011	1.421	10	14
Female indicator variable	28,847	.492	.500	0	1
Hours	28,842	3.763	10.796	0	98
Working strictly positive hours indicator variable	28,842	.139	.346	0	1
Working at least 20 hours per week indicator variable	28,842	.105	.306	0	1
Urban indicator variable	28,847	.774	.418	0	1
Schooling indicator variable	28,841	.925	.263	0	1
Only school indicator variable	28,841	.822	.383	0	1
School and work indicator variable	28,836	.102	.303	0	1
Only work indicator variable	28,842	.024	.153	0	1
No school, no work indicator variable	28,836	.050	.218	0	1
Years of schooling	28,830	3.341	1.946	0	9
Age started work	4,542	10.055	1.997	4	14
Fathers' variables:					
Age	28,847	43.824	9.225	25	98
Years of schooling	28,801	4.920	4.559	0	17

Age started work	27,125	12.134	3.688	4	40
Earnings	28,300	521.001	905.135	0	40,000
Child labor (age 14 or younger)	28,847	.706	.456	0	1
Child labor (age 10 or younger)	28,847	.394	.489	0	1
Not in labor market	28,814	.100	.300	0	1
Mothers' variables:					
Age	28,847	39.602	7.748	25	91
Years of schooling	28,744	5.035	4.375	0	17
Age started work	17,075	13.900	5.784	4	56
Earnings	28,710	143.869	445.588	0	20,000
Child labor (age 14 or younger)	28,847	.372	.483	0	1
Child labor (age 10 or younger)	28,847	.203	.402	0	1
Not in labor market	28,831	.462	.499	0	1
Grandparents' variables:					
Paternal grandfather's schooling (years)	22,085	2.016	2.949514	0	17
Paternal grandmother's schooling (years)	23,813	1.707	2.649685	0	17
Maternal grandfather's schooling (years)	23,470	2.075	2.879995	0	17
Maternal grandmother's schooling (years)	25,059	1.744	2.618133	0	17
Families' variables:					
Family income minus child income	27,953	838.897	1,299.069	0	63,500
No. of boys ages 0–5	28,847	.195	.471	0	5
No. of boys ages 6–9	28,847	.267	.514	0	4
No. of boys ages 10–14	28,847	.863	.771	0	4
No. of boys ages 15–17	28,847	.252	.495	0	3
No. of girls ages 0–5	28,847	.191	.469	0	5
No. of girls ages 6–9	28,847	.266	.515	0	3
No. of girls ages 10–14	28,847	.835	.763	0	5
No. of girls ages 15–17	28,847	.209	.455	0	4

Notes

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1. For a useful survey of both the theoretical and empirical literature, see Kaushik Basu, "Child Labor: Cause, Consequence, and Cure," *Journal of Economic Literature* 37, no. 3 (1999): 1083–1119.

2. See, e.g., Jean-Marie Baland and James A. Robinson, "Is Child Labor Inefficient?" *Journal of Political Economy* 108, no. 4 (2000): 663–79; Basu; Clive Bell and Hans Gersbach, "Child Labor and the Education of a Society," IZA Discussion Paper no. 338 (Institute for the Study of Labor [IZA], Bonn, 2001); Luis Felipe Lopez-Calva and Koji Miyamoto, "Filial Obligations, and Child Labor," *Review of Development Economics* (in press); Priya Ranjan, "Credit Constraints and the Phenomenon of Child Labor," *Journal of Development Economics* 64, no. 1 (2001): 81–102. This is also closely linked to the idea of poverty traps such as the one illustrated in Oded Galor and Joseph Zeira, "Income Distribution and Macroeconomics," *Review of Economic Studies* 60, no. 1 (1993): 35–52.

3. See, e.g., Ranjan Ray, "Analysis of Child Labour in Peru and Pakistan: A Comparative Study," *Journal of Population Economics* 13, no. 1 (2000): 3–19, and "Child Labor, Child Schooling and Their Interaction with Adult Labour: The Empirical Evidence and Some Analytical Implications," *World Bank Economic Review* 14, no.

2 (2000): 347–67; Peter Jensen and Helena Skyt Neilsen, "Child Labour or School Attendance? Evidence from Zambia," *Journal of Population Economics* 10, no. 4 (1997): 407–24; Harry Anthony Patrinos and George Psacharopoulos, "Family Size, Schooling and Child Labor in Peru—an Empirical Analysis," *Journal of Population Economics* 10, no. 4 (1997): 387–405; George Psacharopoulos, "Child Labor versus Educational Attainment: Some Evidence from Latin America," *Journal of Population Economics* 10, no. 4 (1997): 377–86; and Christian Grootaert and Ravi Kanbur, "Child Labor: An Economic Perspective," *International Labour Review* 134, no. 2 (1995): 187–203.

4. Kaushik Basu and Pham Hoang Van, "The Economics of Child Labor," *American Economic Review* 88, no. 3 (1998): 412–27.

5. Ibid.

6. Ibid.

7. This is, of course, not always necessarily true. Children may make their own decisions if they are homeless, orphaned, runaways, or particularly independent. See, e.g., Jane Humphries, "Cliometrics, Child Labor, and the Industrial Revolution," *Critical Review* 13, nos. 3–4 (1999): 269–83.

8. This model is related to the model of household education choice developed in Gerhard Glomm, "Parental Choice of Human Capital Investment," *Journal of Development Economics* 53, no. 1 (1997): 99–114.

9. This assumption follows in the tradition of Gary Becker's theory of the family in his *Treatise on the Family* (Cambridge, Mass.: Harvard University Press, 1982).

10. This assumes, of course, that the wage rate is unaffected by the supply of skilled labor. This is a strong assumption, but the essential results would not change if we made the wage a function of skilled labor supply.

11. Ray, "Analysis of Child Labour in Peru and Pakistan."

12. One could alternately assume that education choice is "lumpy," meaning that parents consider education to be a choice of literacy, primary education, or attaining a high school diploma.

13. Pesquisa Nacional por Amostragem a Domicilio assigns each individual to a position or "condition" in the family. They are: (1) person of reference, (2) spouse, (3) son or daughter, (4) other relative, (5) aggregate, (6) pensioner, (7) domestic worker, and (8) relative of the domestic worker.

14. This selection criterion may impose some selection bias if, e.g., children in families with single heads of households are more likely to work. However, similar results were obtained when a full sample of children 10–14 years old was used. In this case, the characteristics of the head of the family were used instead of the father's and mother's characteristics. Since we want to capture the separate impacts of the father's and the mother's child labor status and to have a straight interpretation of the coefficients, we present the results with the sample described in the text. Probit results with this alternative sample are available on request.

15. Pesquisa Nacional por Amostragem a Domicilio asks the usual hours worked per week for each individual working during the survey week.

16. All results presented in this article come from the unweighted sample. We replicated all of the empirical tests here using a weighted sample and obtained qualitatively the same results.

17. See Christian Grootaert and Harry Anthony Patrinos, eds., *Policy Analysis of Child Labor: A Comparative Study* (New York: St. Martin's, 1999).

18. Ibid.

19. The selection of a binary choice model is natural since we are interested in obtaining the probability of a child working in the labor force. We opt for a nonlinear regression model, because such models are better suited for the case where the dependent variable is clustered either at zero or one. The most common of these are the probit and logit models. The probit model assumes that the error term is standard-

normally distributed, and the logit model assumes that the error term follows the logistic distribution. Because the cumulative normal distribution and the logistic distribution are very close to each other, except at the tails, we are not very likely to get different results; therefore, we feel that both models are equally suited to estimate the predicted probability of a child working as a laborer. As a check of this assumption, we estimated both models and found that the results were qualitatively the same. In this article, we present the results that we obtained from estimating the probit model. For readers interested in the results that we obtained from estimating the logit specification, they are available on request.

20. The inclusion of the indicator variables of a parent not in the labor market accounts for the fact that for those parents not in the labor market, the age at which they started to work is unknown.

21. A similar model was estimated for the case when child labor is defined as a child who worked at least 20 hours in the week of reference. We obtained qualitatively the same results.

22. In our sample, roughly 10% of men and 46% of women were not in the labor market. There seems to be no reason, a priori, to think that these individuals would be more or less likely to have been child laborers. However, the fact is that we do not observe the child labor history of those not in the labor market. Hence, for those, we assign the parent child labor status equal to zero. To control for the potential bias that this assignment may create, we also introduce a dummy variable equal to one for those parents who are not in the labor market. Still, in the extreme case where they all were child laborers, the negative and significant sign on the not-in-the-labor-market variables for fathers and mothers could counteract the positive coefficient on the parental child labor variable and could mean that the net effect of child labor status is insignificant. As only 10% of fathers are not in the labor market, it seems very unlikely that this would be the case, but it is potentially a problem for the effect of maternal child labor.

23. Pesquisa Nacional por Amostragem a Domicilio 1996 presents the educational attainment of the grandparents in 10 categories. We converted these categories into years of schooling in the following way:

Category	*Years of Schooling*
No school or incomplete first grade, first-grade degree	0
Incomplete elementary or complete first–third grade, first-grade degree	2
Complete elementary or complete fourth grade, first-grade degree	4
Incomplete half first cycle or fifth–seventh grade, first-grade degree	6
Complete half first cycle or complete eight grade, first-grade degree	8
Incomplete half second cycle or incomplete second-grade degree	9.5
Complete half second cycle or complete second-grade degree	11
Incomplete superior	13
Complete superior	15
Complete master or doctorate	17

24. For an excellent summary of duration models, and particularly the Cox proportional hazard model, see Nicholas Kiefer, “Economic Duration Data and Hazard Functions,” *Journal of Economic Literature* 26, no. 2 (1988): 646–79.

25. We assume “child laborers” to be those respondents who reported an age at which they entered the labor force. In some cases, we have observations on children who were not working during the reference week but nevertheless reported an age at

which they entered the labor force. To check robustness, we also estimated the same model considering only the children who reported the age at which they started working *and* were working in the week of reference as a child laborer. The results were qualitatively the same.

26. Bell and Gersbach (n. 2 above) present an excellent analysis of exactly this type of government plan.