Is There a Child Labor Trap?
Inter-Generational Persistence of Child Labor in Brazil

Patrick M. Emerson
Department of Economics
Cornell University
Ithaca, NY 14853
pme4@cornell.edu

André Portela F. de Souza
Department of Economics
Cornell University
Ithaca, NY 14853
aps11@cornell.edu

May 2000

Abstract

This paper examines inter-generational persistence in child labor by developing a dynamic model and exploring its implications empirically in Brazil. We begin by building an overlapping generations model of the household child labor decision. We assume that this decision is made by the head of the household, where 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. The main predictions of the model are that children are more likely to work when they come from households with parents who were child laborers, from households with parents who have lower educational attainment and that child labor has adverse effects on children's educational attainment and their adult earnings.

Evidence of persistence in child labor is found by examining household survey data from Brazil. We exploit the fact that the survey data includes information on child labor of both parents and children in a household, as well as information on the educational achievement of the grandparents. We find that people who start work at an younger age end up with lower educational outcomes, that those who start work at a younger age end up with lower earnings as adults, and that children are more likely to be child laborers the younger their parents were when they entered the labor force and the lower the educational attainment of the parents.

(**JEL classification numbers:** J20, O12, O54)

(**Keywords:** Child Labor, Brazil)

Is There a Child Labor Trap?
Inter-Generational Persistence of Child Labor in Brazil

I. Introduction

Child labor is a widespread phenomena in the world's economies and has been for generations. Recently, child labor has been put in the spotlight by activists, politicians and economists alike. Most of the popular discussion has centered around the harmful effects of child labor and ways to curtail its incidence. Much of the recent theoretical literature in economics (see Basu, 1999, for a useful survey of the both the theoretical and empirical literature) has focused attention on how child labor is most likely a household decision. Most of the previous empirical literature has focused solely on isolating the determinants of child labor using survey data.

The main insight of the recent literature on child labor is this focus on examining the household as the decision-making unit. If, in fact, it is the head of the household that makes the child labor decision, as is now commonly assumed, then this raises interesting questions about the inter-generational link in child labor. There has been some preliminary theoretical work examining this link (Basu, 1999; Bell and Gersbach, 2000) but there is a marked absence of empirical work on the topic. This paper is an attempt to examine this link both theoretically and empirically.

This paper examines inter-generational persistence in child labor. We begin by building a overlapping generations model of the household child labor decision. Following Basu and Van (1998), we begin by assuming that the child labor decision is made by the head of the household. In addition, 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. This is slightly different than the "luxury axiom" in Basu and Van (1998). In our case the decision is not made on the basis of the families current consumption relative to a poverty line, rather it is an inter-generational comparison of current versus future consumption.

We begin with a model where 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 of the adult. A child can either go to school and/or work. The amount of time spent working detracts from the total educational attainment of the child and thus diminishes the child's earnings once he/she reaches adulthood. Thus families with little education are more desperate for the contribution to current consumption the child can provide than are families with high education, and therefore it is the low education families that will send their children to work while high education families will not.

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 survey data includes information on child labor of both parents and children in a household as well as information on the educational achievement of the grandparents. We find that people who start work at an earlier age end up with lower educational outcomes, that those who start work at a younger age end up with lower earnings as adults, and that children are more likely to be child laborers the younger their parents were when they entered the

labor force, and the less education of the grandparents. These findings are all consistent with our model of child labor persistence.

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 important as it demonstrates that 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 stark contrast to many current policies that suggest resources be directed to all children generation after generation. As Basu and Van (1998) demonstrate, 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. This paper demonstrates that, in this case, appropriate policy response is to concentrate on the condition of each family rather than focusing on individual children.

II. The Model

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), and upon 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 or not to send the child to work (and thus forgo at least some education). In addition, total human capital accumulation (from total education as a child) is the sole determinate of adult wage. We shall normalize the child

wage to 1 and this is assumed to be the same as the wage for an adult worker with no education.

We shall first present a general model and after, a specific model with an analytic solution. This model is closely related to the model developed by Glomm (1997) in that the adult makes the education choice for the child.

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

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

where c_t is the period t consumption of the family and h_{t+1} is the human capital achievement of the child.

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 income of the adult and h_t is the stock of human capital of the adult. 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 1, so a child who spends all of his or her time working will earn \$1. Generally, 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, and e_t is the time spent in school, and $e_t \in [0,1]$. Total family earnings at time t is given then 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 non-satiation 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 $f'(e_t) > 0$ for all $e_t \in [0,1]$.

We can substitute the constraints into the objective function (1) and derive the adults problem:

$$\max_{\{e_t\}} \quad U_t(h_t + 1 - e_t, f(e_t)). \tag{7}$$

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:

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

and the law-of-motion is then:

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

Consider a Φ function that is shaped as in Figure 1. Here there arise multiple 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 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

eventually reach the steady state of $h_t = \bar{h}$, where the children do no work and attend school full-time.

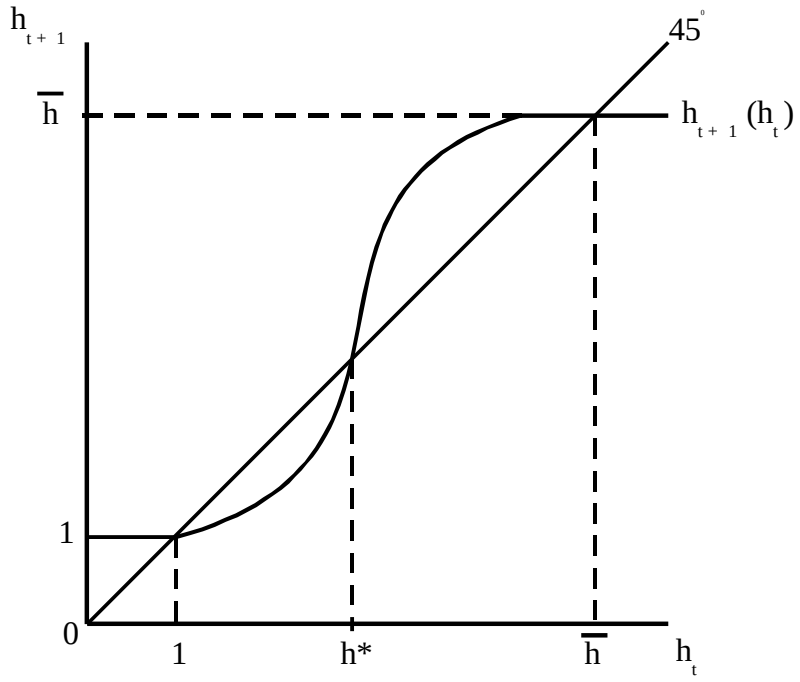

Figure 1

To give a more concrete example consider a utility function of the Cobb-Douglas type:

$$U_t(c_t, h_{t+1}) = c_t^{\alpha} h_{t+1}^{1-\alpha}, \quad \alpha \in (0,1) \qquad (1')$$

and where (2), (3), (4) and (5) are all the same. But suppose now that education choice is "lumpy," where you can only choose to go to school full-time or not at all, for example.[1] This strikes us as a very realistic, though polar, assumption. There may be many intermediate levels, but a people generally make decisions about whether to continue education after reaching a certain level and for simplicity we shall assume a simple binary choice. Since 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, one would expect few people selecting a level of education between primary school and secondary school. We can capture this idea with a new technology that converts education into adult human capital like the following:

$$h_{t+1} = \begin{cases} \Theta, & if \quad e_t = 1 \\ 1, & if \quad e_t = 0 \end{cases} \qquad (6')$$

where $e_t \in \{0,1\}$, and $\Theta > 1$. Θ can be interpreted as returns to education or simply as the educated adult wage rate. Again, if an adult has no education then he or she commands a wage of 1, the same as a child laborer.

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:

$$U_t^{e_t=1} \geq U_t^{e_t=0}. \qquad (10)$$

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

[1] One could alternately assume that returns to education are "lumpy," meaning that ones future earnings are not a continuous function of childhood education, rather there exist discrete jumps.

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

Which reduces to:

$$h_t \geq \frac{1}{\Theta^{\frac{1-\alpha}{\alpha}} - 1} \equiv h^*. \quad (12)$$

So (12) defines the critical value h^* where adults that have human capital h^* and above will send their children to school full time and those that do not will send their kids to work full time. Thus there are two steady-state equilibria in this model, at full education and at no education. This is illustrated in Figure 2.

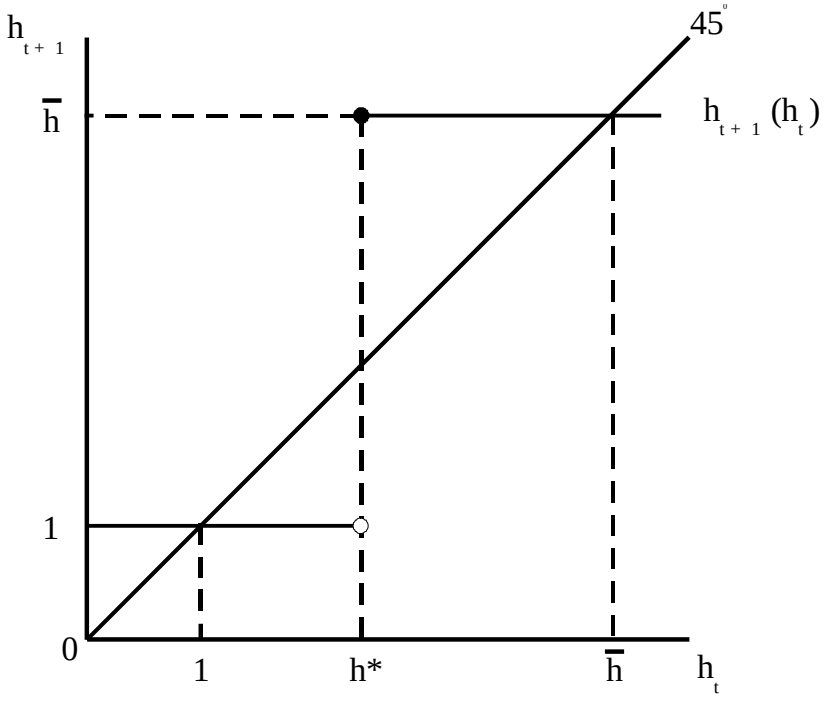

Figure 2

For a wide range of parameterizations, $h^* \in (1, \Theta)$. For example if $\Theta = 1.75$ and $\alpha = 0.5$, then $h^* = 1.33\overline{3}$. It is also interesting to note that h^* is increasing in α, and

decreasing in Θ. Thus the more weight the adults places on current consumption as opposed to the child's human capital achievement, the more likely the adult is to make 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 model presents a polar version of the child labor choice, we believe it illustrates well the fundamental inter-generational link between child labor of the parents and their offspring, a link that we shall explore empirically in the next section.

III. Empirical Evidence from Brazil

3.1 The Data

The data used in this study come from the 1996 Brazilian Household Surveys called *Pesquisa Nacional por Amostragem a Domicilio* (PNAD) 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 U.S. 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. This sampling design generates annual samples of approximately 100,000 households.

The sample selection of this study consists of individuals between 10 and 14 years old that are considered a son, daughter or other relative in the family unit.[2] Each observation consists of information on the child characteristics, his or her parent

characteristics and his or her family characteristics. Since we are primarily concerned with the impact of parent's child labor status on the child labor status of the kid, we use a workable sample of observations with complete information of the father's and the mother's characteristics. Due to this criterion, families with single heads are excluded from the analysis.[3]

The child labor variables for the kids are constructed as follows. A child is considered to work if he or she worked on the labor market any strictly positive hours in the survey week of reference. Moreover, A child is considered to work full time if he or she worked 20 hours or more on the labor market in the week of reference. Both definitions of child labor will be used to check the robustness of the results.

The child labor variable for the parents is defined as follows. The PNAD survey asks each individual the age at which he or she start to work Thus, if a parent began working in the labor market at 14 years old or below, he or she is considered to have been a child laborer.

For each child, we also obtain his or her school attendance status, race, gender and region of residence. Similarly, we constructed years of schooling, age and employment status of the parents. The definitions of all variables used in the analysis are reported in the appendix.

---

[2] PNAD assigns each individual to a position or 'condition' in the family. They are (i) person of reference; (ii) spouse; (iii) son or daughter; (iv) other relative; (v) aggregate; (vi) pensionist; (vii) domestic worker; and (viii) relative of the domestic worker.

[3] This selection criterion may impose some selection bias if , e.g., kids in single head families are more likely to work. However, similar results were obtained when a full sample of 10 to 14 years old children were used. In that case the head of the family's characteristics were used instead of the father and mother's characteristics. Since we want to capture separate impacts of the father and the mother's child labor status, we present the results with the workable sample above.

Table 1: Unconditional Probabilities of Inter-Generational Child Labor Persistence.

workmj		*chl14d*			*chl14m*		
		0	1	Total	0	1	Total
0	Number	8207	17389	25596	17216	8380	25596
	Row %	32.06	67.94	100	67.26	32.74	100
	Column %	94.04	82.77	86.07	92.11	75.86	86.07
1	Number	520	3621	4141	1474	2667	4141
	Row %	12.56	87.44	100	35.6	64.4	100
	Column %	5.96	17.23	13.93	7.89	24.14	13.93
Total	Number	8727	21010	29737	18690	11047	29737
	Row %	29.35	70.65	100	62.85	37.15	100
	Column %	100	100	100	100	100	100

Table 1 presents the proportions of child labor and adult's child labor status in 1996. Of all 10 to 14 year old children in the sample, 13.9 percent worked in the labor market. 70.6 percent of their fathers were child laborers and 37.2 percent of their mothers started working at age 14 or below. More importantly, of all child workers, 87.4 percent come from a family in which the father was a child laborer, and 64.4 percent belong to a family where the mother was a child laborer. Although these results are unconditional probabilities, they strongly suggest the existence of inter-generational persistence in child labor in Brazil.

3.2 The Empirical Models

To test the inter-generational effect of child labor we estimate four different models. The first is a probit of child labor on parents child labor status and a vector of other controls. The second is a linear regression of the age at which the child entered the labor force against the age at which the parents started work 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 (see Grootaert and Patrinos, 1999). In order to account for this decision structure, we estimate two different models, which depend on the assumptions of the decision making process. Thus, the third model uses a sequential probit model following Grootaert and Patrinos (1999) in which the school versus work decisions are assumed to be made sequentially. The fourth model is a multinomial logit model which assumes that the decision is made on all of the options simultaneously. Given that we are primarily concerned with the child labor persistence, and that the main results hold for all models, we will present the first two models in the text and refer the reader to the appendix for the sequential probit and multinomial logit results. We believe that the two models presented below are sufficient evidence to support our main hypothesis.

3.2.1. The Inter-Generational Persistence of Child Labor

To estimate the effect of parental child labor on the incidence of work among youths aged 10-14, we first estimate a standard probit model. The dependent variable is an indicator that equals one if the child worked any strictly positive hours in his/her main job in the week of reference[4]. This is regressed on indicator variables that equal one if the child's mother and father were child laborers, variables for the number of years of schooling of each of the parents and interaction terms which multiply the parent's child labor indicator variables with their years of schooling. Also included is the age of the child, the age of the parents, the number of brothers and sisters aged 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 that

[4] The week of reference of PNAD 1996 is from 09/22/96 to 09/28/96.

does not work, has a mother that does not work[5]. The results are shown in the first column of Table 2.

We find that parental child labor has a strongly positive effect on the probability that a child is in the labor force, that the years of schooling of the parents have a strongly negative effect and that coefficient on the fathers child labor and years of schooling interactive variable is positive and significant. These results indicate that a child is more likely to be laborer if his/her parents were child laborers, less likely the more educated are his/her parents and that the marginal effect of education of the father having been a child laborer is negative but smaller if he was a child laborer. Moreover, a female child or a child in urban areas is less likely to work in the labor market. Also, the greater the number of siblings aged 5 to 14, the more likely the child is to work.

In order to evaluate the impact of the grandparents' education on child labor status of the grandson or granddaughter, we also estimate two probit models that include the years of schooling of grandparents as explanatory variables. Column 3 of Table 2 presents the results of a regression that excludes parents' education and the interaction of their education and their child labor status. Column 5 of Table 2 shows the coefficients from the complete set of regressors. When we exclude the years of schooling of parents, we find that the more educated the grandparents are, the less likely to work the child is. However, 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 child labor status of the grandchild. This effect appears to operate through the education of the parents only.

[5] Similar model was estimated for the case when child labor is defined as a child that worked at least 20 hours in the week of reference. We obtained qualitatively the same results.

3.2.2. The Effect of Age Started Working

An alternative way to evaluate the inter-generational persistence of child labor is to estimate the effect of the age at which the parents entered the labor force on the age at which the child starts to work. We expect that, *ceteris paribus*, the older the parents entered the labor market the older the child began working. For this we estimate a linear regression where the dependent variable is a continuous variable of the age the child started working and the independent variables are the same as in the probit models except that now the variables for the parent's child labor are continuous variables for the age at which each entered the labor force and those variables squared. Also the interactive terms now interact the age the parents entered the labor force with their education.

Note however that the dependent variable is censored since we only observe the age started working of those children that are actually in the work force. To account for this selectivity bias we additionally estimate a Heckman selection model where the additional variables in the first step are indicator variables that equal one if the father (mother) does not work. The results of both models are shown in Table 3.

Again, the results for all models are essentially the same. The age at which they entered the labor force for both father and mother has a positive effect on the age at which the child enters the labor force but the marginal effect declines as the parents enter later. Years of schooling for both parents has a positive effect on the age the child starts working but the coefficients are no longer significant (father is at the 10% level). When we perform a heckman correction the years of school of the mother becomes significant. Once more, the grandparents' years of schooling have no direct impact on the age at which the child starts to work, as revealed by the last two models of Table 3.

3.3 Cost of Child Labor

So far we have shown strong evidence of inter-generational persistence of child labor in Brazil. However, in order to explain why we should be concerned with 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 future earnings.

In order to assess the impact of having been a child laborer on current earnings, we estimate a simple OLS regression and a Heckman selection model for both mothers and fathers in the sample, separately. Here we regress the log of current earnings on years of schooling, age and age squared, age they started work and its square, an interaction of years of schooling and age started work, and the race and urban indicator variables. For the selection-bias corrected estimations we add the family composition variables in the first stage regression. The results are given in Table 4.

For both fathers and mothers the coefficient on the age they started work is positive and significant. Meaning that child labor has a negative impact on current earnings controlling for education and other variables. This means that the negative aspects of loosing out on education outweigh the possible positive effects of gaining experience as a child laborer. The squared term is negative meaning that the impact lessens the older the individual enters the labor force.

Because of the age started work – years of schooling interaction term, the optimal age to start work depends on the years of schooling. For a male with no schooling, the optimal age is 12, with four years of schooling (the end of primary education), 16, and

with eight years (the end of secondary education), 19. So for an illiterate male it is better to start working as a child, but when one considers the work – school tradeoff this means that the individual is forgoing future earnings from the attainment of more human capital. For a female the age started work – years of schooling interaction term is not significant, so for any level of schooling the optimal age to start work is 20 years old.

IV. Conclusion

This paper presents an overlapping generations model of inter-generational child labor persistence and finds strong evidence of such a link in Brazil. The results suggest that there is a significant relationship between parent's child labor incidence and 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, children attain higher levels of education the more education their parents have. 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. Finally, earnings as an adult are lower, ceteris paribus, the earlier the individual enters the labor market. Together, these results paint a striking picture of the inter-generational persistence and harmful effects of child labor within families.

This suggests that the household should be treated as a whole when it comes to designing policies aimed at reducing the incidence of child labor. These policies are important because in this paper we also show that child labor has harmful effects on individual's earnings abilities as adults. Thus the negative effect of the loss of

educational attainment is greater than the positive effect of gaining experience as a child laborer.

So what is shown in this paper is 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 his of her own child to work. Thus the cycle continues. It is important then to break this cycle within each household in order to achieve a lasting, long run, reduction in child labor in a society. Policies that are able to break this cycle, family by family are potentially the most effective instrument to reduce the incidence of child labor. This type of policy would likely involve a one-time transfer of a critical level of resources to a family rather than continual support of children's education.

Appendix A: Sequential Probit and Multinomial Logit Models

In this appendix we consider the child labor decision to work as a joint decision to attend school.

1. Sequential Probit

This model considers the work v. school choice to be a sequential choice and therefore we estimate a sequential probit model. Here we consider a choice structure where households first decide whether to send the child to school full-time, then, if not, whether to send the child to school part-time and to work part-time, then, if not, whether to send the child to work full-time or have the child neither work nor go to school. To do this we estimate a sequence of conditional probits where the first includes all observations, the second excludes those who are in school full-time and the third excludes those that either go to school full-time or go to school part-time and work part-time. These results are given in Table A1.

The pattern in the sequential probit model is the same as the normal probit for the school full-time versus all other choices. That is, parents having been child-laborers has a negative effect on the probability the child goes to school full-time and that the more years of schooling the parents have the more likely the child will attend school full-time. When the choice is to go to school part-time and work part-time versus going to school full-time or doing nothing some interesting results occur. The child labor and schooling variable of the father are no longer significant. The mother having been a child laborer, and having more schooling, has a positive effect on the probability that the child will attend school part-time and work part time versus no school at all (work full-time or do nothing). Finally when the decision is to work full-time or do nothing, the coefficient is

positive and significant on the mother having been a child laborer indicator variable and negative and significant on the fathers years of schooling.

2. Multinomial Logit

The multinomial logit model considers the same choices as above, but this time assumes that households make this choice at one time (rather than sequentially). To test this a new variable is created that equals 1 if the individual is in school full time, 2 if the individual is in school part time and works part time, 3 if the individual works full time and 4 if the individual neither works nor goes to school. The multinomial logit model is then run on this variable. These results are given in Table A2.

The results here follow the same general pattern as the normal probit. Parents having been child laborers has a positive effect on the probability that the child will be in the labor force, and parents years of schooling has a negative effect. The interactive term for the father is positive and significant for the work and school choice (relative to the full time school choice).

Appendix B: List of Variables

workmj	Indicator variable equals 1 if individual works in the labor market
schft	Indicator variable equals 1 if individual is in school full time
schwk	Indicator variable equals 1 if individual is in school and works in the labor market
wkft	Indicator variable equals 1 if individual works full time
worksch	Variable that equals 1 if individual is FT school, 2 if PT school – PT work, 3 if FT Work and 4 if no school and no work.
chl14d	Indicator variable equals 1 if individual's father was a child laborer
chl14m	Indicator variable equals 1 if individual's mother was a child laborer
aswd	Age the father started working
asw2d	aswd squared
aswm	Age the mother started working
asw2m	aswm squared
yearschd	The years of schooling of the father
yearschm	The years of schooling of the mother
aswdsch	Variable interacting aswd with yearschd
aswmsch	Variable interacting aswm with yearschm
c14ysd	Variable interacting chl14d with yearschd
c14ysm	Variable interacting chl14m with yearschm
age	The age of the individual
schlgdd	The years of schooling of the grandfather from father's side
schlgmd	The years of schooling of the grandmother from the father's side
schlgdm	The years of schooling of the grandfather from mother's side
schlgmm	The years of schooling of the grandmother from the mother's side
female	Indicator variable equals 1 if individual is female
urban	Indicator variable equals 1 if individual lives in an urban area
nworkmjd	Indicator variable equals 1 if individual's father is not working
nworkmjm	Indicator variable equals 1 if individual's mother is not working
aged	Age of the father
agem	Age of the mother
b05	Number of boys in the family aged 0 to 5 years
b69	Number of boys in the family aged 6 to 9 years
b1014	Number of boys in the family aged 10 to 14 years
b1517	Number of boys in the family aged 15 to 17 years
g05	Number of girls in the family aged 0 to 5 years
g69	Number of girls in the family aged 6 to 9 years
g1014	Number of girls in the family aged 10 to 14 years
g1517	Number of girls in the family aged 15 to 17 years

REFERENCES

Basu, Kaushik. (1999) "Child Labor: Cause, Consequence, and Cure," *Journal of Economic Literature*, 37:3, pp.1083-1119.

Basu, Kaushik, and Pham Hoang Van. (1998) "The Economics of Child Labor," *American Economic Review*, 88:3, pp. 412-427.

Bell, Clive, and Hans Gersbach. (2000) "Child Labor and the Education of a Society." *mimeo.*

Glomm, Gerhard. (1997) "Parental Choice of Human Capital Investment," *Journal of Development Economics*, 53:1, pp. 99-114.

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

Table 2: Child Labor Persistence. Probit on Child Labor Indicator Variable.

Independent Variables	*Coefficient*	*Std. Deviation*	*Coefficient*	*Std. Deviation*	*Coefficient*	*Std. Deviation*
chl14d	0.199**	0.043	0.280**	0.038	0.168**	0.056
chl14m	0.309**	0.037	0.369**	0.034	0.298**	0.047
yearschd	-0.040**	0.007			-0.039**	0.009
yearschm	-0.032**	0.005			-0.037**	0.007
c14ysd	0.014*	0.007			0.016	0.009
c14ysm	0.002	0.006			0.005	0.008
age	0.213**	0.008	0.214**	0.010	0.215**	0.010
schlgdd			-0.015	0.008	0.001	0.009
schlgmd			-0.021*	0.009	-0.004	0.009
schlgdm			-0.017*	0.008	-0.002	0.008
schlgmm			-0.018*	0.008	0.001	0.009
female	-0.597**	0.032	-0.592**	0.041	-0.591**	0.041
urban	-0.720**	0.023	-0.798**	0.029	-0.729**	0.029
nworkmjd	-0.234**	0.046	-0.196**	0.060	-0.254**	0.061
nworkmjm	-0.363**	0.028	-0.309**	0.035	-0.371**	0.036
aged	0.004**	0.002	0.004*	0.002	0.002	0.002
agem	0.000	0.002	0.004	0.002	0.003	0.002
b05	0.044*	0.021	0.030	0.028	0.014	0.028
b69	0.083**	0.020	0.073**	0.026	0.058*	0.026
b1014	0.059**	0.017	0.056*	0.022	0.042	0.022
b1517	0.015	0.020	0.056*	0.026	0.041	0.026
g05	0.088**	0.021	0.138**	0.026	0.118**	0.026
g69	0.095**	0.020	0.135**	0.024	0.113**	0.025
g1014	0.046**	0.018	0.042	0.023	0.023	0.023
g1517	-0.043	0.023	-0.034	0.029	-0.044	0.029
constant	-3.184**	0.123	-3.605**	0.151	-3.146**	0.157
Number of Observations	29558		18301		18216	
Chi-Squared (n)	4155 (21)		2543 (21)		2563 (25)	
Psuedo R-squared	0.24		0.24		0.25	

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

Table 3: OLS and Heckman Model Estimates on the Age the Child Started Working

Model	**OLS**		**Heckman**		**OLS**		**Heckman**		**OLS**		**Heckman**	
Indep. Variables	*Coef.*	*Std. Dev.*	*Coef.*	*Std. Dev.*	*Coef.*	*Std. Dev.*	*Coef.*	*Std. Dev.*	*Coef.*	*Std. Dev.*	*Coef.*	*Std. Dev.*
aswd	0.390**	0.053	0.312**	0.046	0.380**	0.063	0.298**	0.054	0.359**	0.064	0.284**	0.056
asw2d	-0.013**	0.002	-0.006**	0.002	-0.012**	0.003	-0.005*	0.002	-0.010**	0.003	-0.005*	0.002
aswm	0.175**	0.023	0.171**	0.020	0.182**	0.028	0.194**	0.023	0.191**	0.029	0.192**	0.025
asw2m	-0.004**	0.001	-0.002**	0.000	-0.004**	0.001	-0.002**	0.001	-0.004**	0.001	-0.002**	0.001
yearschd	0.058	0.032	0.040	0.037					0.107**	0.041	0.057	0.045
yearschm	0.041	0.026	0.116**	0.030					0.056	0.032	0.131**	0.037
aswdsch	-0.003	0.003	0.000	0.003					-0.008*	0.003	-0.002	0.004
aswmsch	-0.002	0.002	-0.001	0.002					-0.003	0.002	-0.002	0.003
schlgdd					0.013	0.026	0.043	0.029	0.010	0.026	0.015	0.029
schlgmd					0.001	0.026	0.007	0.030	-0.004	0.028	-0.020	0.031
schlgdm					0.031	0.024	0.063*	0.027	0.021	0.025	0.028	0.028
schlgmm					-0.028	0.024	0.018	0.028	-0.032	0.025	-0.024	0.028
age	0.539**	0.020	0.259**	0.026	0.491**	0.026	0.216**	0.033	0.490**	0.026	0.220**	0.032
female	0.121	0.081	1.209**	0.108	0.195	0.102	1.274**	0.135	0.187	0.102	1.236**	0.134
urban	0.826**	0.060	2.322**	0.086	1.019**	0.075	2.630**	0.106	0.979**	0.077	2.453**	0.106
aged	-0.004	0.004	-0.007	0.005	-0.005	0.005	-0.007	0.007	-0.002	0.005	0.000	0.007
agem	-0.003	0.005	-0.002	0.006	-0.002	0.006	-0.009	0.008	-0.001	0.006	-0.007	0.008
b05	0.031	0.052	0.008	0.068	0.042	0.067	0.051	0.086	0.052	0.067	0.079	0.086
b69	-0.183**	0.048	-0.271**	0.062	-0.154*	0.064	-0.199*	0.081	-0.148*	0.064	-0.163*	0.081
b1014	-0.081	0.043	-0.227**	0.055	0.000	0.053	-0.122	0.068	0.006	0.053	-0.093	0.068
b1517	0.057	0.051	0.070	0.066	0.064	0.065	-0.001	0.084	0.074	0.065	0.043	0.083
g05	-0.081	0.050	-0.224**	0.067	-0.160*	0.063	-0.414**	0.085	-0.146*	0.064	-0.361**	0.084
g69	0.009	0.048	-0.164**	0.062	-0.069	0.059	-0.313**	0.078	-0.053	0.060	-0.244**	0.078
g1014	-0.047	0.044	-0.155**	0.057	-0.027	0.058	-0.137	0.074	-0.016	0.058	-0.075	0.073
g1517	0.055	0.057	0.033	0.073	0.036	0.071	0.025	0.091	0.034	0.071	0.050	0.090
constant	-0.912*	0.435	4.375**	0.508	-0.348	0.531	5.119**	0.596	-0.727	0.541	4.359**	0.625
Nu. of Obs.	3552		16736		2192		10426		2183		10369	
R-squared	0.34				0.34				0.34			
Chi-sq. (n)			2367 (21)				1587 (21)				1562 (25)	

* Statistically significant at the 5% level. ** Statistically significant at the 1% level.

Table 4: Effect of Child Labor on Log of Adult Earnings of Fathers and Mothers. OLS and Heckman Model Estimates. (Indicator Variables for Occupation and Industry Included)

	OLS		Heckman	
Independent Variables (Father)	*Coefficient*	*Std. Deviation*	*Coefficient*	*Std. Deviation*
yearschd	0.083**	0.004	0.083**	0.004
aged	0.056**	0.004	0.054**	0.004
age2d	-0.001**	0.000	-0.001**	0.000
aswd	0.016**	0.006	0.016*	0.006
asw2d	-0.001**	0.000	-0.001**	0.000
aswdsch	0.001**	0.000	0.001**	0.000
nowhited	-0.248**	0.009	-0.246**	0.009
urban	0.205**	0.014	0.208**	0.014
constant	3.984**	0.100	4.198**	0.109
Number of Observations	25505		27940	
R-squared	0.50			
Chi-squared (n)			24363 (25)	
Independent Variables (Mother)	*Coefficient*	*Std. Deviation*	*Coefficient*	*Std. Deviation*
yearschm	0.093**	0.005	0.093**	0.005
agem	0.062**	0.009	0.062**	0.009
age2m	-0.001**	0.000	-0.001**	0.000
aswm	0.030**	0.005	0.030**	0.005
asw2m	-0.001**	0.000	-0.001**	0.000
aswmsch	0.000	0.000	0.000	0.000
nowhitem	-0.245**	0.014	-0.245**	0.014
urban	0.468**	0.022	0.468**	0.022
constant	3.245**	0.190	3.250**	0.230
Number of Observations	11864		17527	
R-squared	0.48			
Chi-squared (n)			10166 (25)	

* Statistically significant at the 5% level. ** Statistically significant at the 1% level.

Table A1: Sequential Probit Model Estimates.

Dependent Variables	**schft**		**schwk**		**wkft**	
Independent Variables	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
chl14d	-0.178**	0.050	-0.005	0.099	-0.077	0.165
chl14m	-0.182**	0.043	0.139	0.079	0.306*	0.127
yearschd	0.039**	0.008	0.012	0.019	-0.117**	0.044
yearschm	0.047**	0.006	0.041**	0.013	-0.063**	0.024
c14ysd	-0.004	0.008	0.027	0.019	0.114*	0.045
c14ysm	-0.003	0.007	0.048**	0.017	-0.020	0.031
age	-0.200**	0.009	-0.007	0.017	0.311**	0.030
schlgdd	-0.005	0.008	-0.041*	0.017	-0.012	0.030
schlgmd	0.007	0.008	0.023	0.019	-0.028	0.029
schlgdm	0.002	0.008	-0.017	0.017	0.053	0.030
schlgmm	-0.007	0.008	0.011	0.018	-0.026	0.032
female	0.397**	0.037	-0.352**	0.068	-0.938**	0.112
urban	0.635**	0.027	-0.130**	0.050	-0.580**	0.086
nworkmjd	0.059	0.051	-0.352**	0.108	-0.321	0.179
nworkmjm	0.210**	0.032	-0.298**	0.066	-0.219*	0.111
aged	-0.002	0.002	0.004	0.003	-0.005	0.005
agem	-0.002	0.002	-0.004	0.004	0.006	0.007
b05	-0.040	0.026	-0.081	0.044	0.044	0.069
b69	-0.063**	0.024	-0.023	0.042	-0.054	0.071
b1014	-0.043	0.020	0.016	0.035	-0.066	0.062
b1517	-0.077**	0.024	0.005	0.044	-0.003	0.074
g05	-0.126**	0.025	-0.024	0.042	0.059	0.065
g69	-0.095**	0.023	-0.026	0.041	0.212**	0.065
g1014	-0.021	0.021	-0.017	0.039	0.076	0.063
g1517	0.014	0.026	-0.061	0.048	-0.054	0.081
constant	2.820**	0.145	0.315	0.274	-3.604**	0.476
Number of Observations	18216		3268		1399	
Chi-squared (n)	2539 (25)		314 (25)		325 (25)	
Pseudo R-squared	0.20		0.08		0.22	

* Statistically significant at the 5% level. ** Statistically significant at the 1% level.

Table A2: Multinomial Logit Model.
Comparison Status is School Full Time (worksch = 1)

Dependent Variable: worksch =	**2 (Work and School)**		**3 (Work Full Time)**		**4 (No Work / School)**	
Independent Variables	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
chl14d	0.296*	0.120	0.134	0.220	0.321*	0.133
chl14m	0.484**	0.097	0.451**	0.169	-0.011	0.121
yearschd	-0.077**	0.019	-0.274**	0.071	-0.084**	0.024
yearschm	-0.060**	0.014	-0.225**	0.039	-0.130**	0.019
c14ysd	0.041*	0.019	0.148*	0.074	-0.041	0.026
c14ysm	0.020	0.016	-0.005	0.048	-0.015	0.027
age	0.375**	0.020	0.728**	0.043	0.239**	0.026
schlgdd	-0.016	0.018	0.055	0.043	0.050*	0.023
schlgmd	0.002	0.019	-0.081	0.052	-0.029	0.027
schlgdm	-0.015	0.018	0.044	0.042	-0.012	0.024
schlgmm	0.018	0.018	-0.064	0.050	0.007	0.026
female	-1.044**	0.083	-1.515**	0.155	0.012	0.106
urban	-1.270**	0.060	-1.538**	0.114	-0.607**	0.079
nworkmjd	-0.500**	0.134	-0.488	0.260	0.318*	0.126
nworkmjm	-0.612**	0.077	-0.347*	0.147	0.003	0.095
aged	0.003	0.004	-0.008	0.008	0.002	0.005
agem	0.002	0.005	0.011	0.009	-0.001	0.006
b05	0.008	0.056	0.106	0.096	0.133*	0.067
b69	0.083	0.051	0.059	0.092	0.134*	0.064
b1014	0.091*	0.043	0.000	0.080	0.066	0.056
b1517	0.123*	0.052	0.063	0.094	0.181**	0.065
g05	0.196**	0.054	0.313**	0.090	0.220**	0.065
g69	0.172**	0.050	0.313**	0.086	0.058	0.066
g1014	0.034	0.047	0.117	0.082	-0.018	0.062
g1517	-0.064	0.059	0.000	0.103	0.066	0.073
constant	-5.617**	0.327	-10.495**	0.686	-4.928**	0.413
Number of Observations	18181		18181		18181	
Chi-squared (n)	4336 (75)		4336 (75)		4336 (75)	
Psuedo R-squared	0.19		0.19		0.19	

* Statistically significant at the 5% level. ** Statistically significant at the 1% level.