Child Labor and the Wealth Paradox: The Role of Altruistic Parents

Luiz Renato Lima[*], Shirley Mesquita[†], Marianne Wanamaker[‡]

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Abstract

Using data from Pakistan, we study the effect of family wealth on the utilization of child labor. We find evidence of a positive relationship between land wealth and child labor only for children in the upper quantiles of the distribution. We hypothesize that the so-called "wealth paradox" in child labor is driven by parental preferences.

Keywords: Child labor; Wealth paradox; Endogeneity; Censored quantile regression.
JEL Classification: C1; J2; J7.

1 Introduction

For policy makers, the underlying cause of child labor in developing nations is a critical issue. Basu and Van (1998) introduced the first decision-making model on child labor and showed the existence of two equilibria in the labor market. In one equilibrium, children work. In the other, adult wages are high and children do not work. A practical consequence of the Basu and Van paper is that child labor would decrease as household resources rise, a result of their "luxury axiom": all else equal, parents would choose to have their children not working rather than working.

But empirical evidence frequently reveals the opposite result, giving rise to what is now called the "wealth paradox". Indeed, Nardinelli (1990) showed that in Britain in the nineteenth century, despite large variations in wage, there was no correlation between adult wages and child labor participation rates. More recently, Bhalotra and Heady (2003) show that in rural Pakistan in the 1990s, the children of land rich households work more then those

[‡]Corresponding author. Department of Economics, University of Tennessee at Knoxville and Federal University of Paraiba-Brazil, 527A Stokely Management Center (e-mail: llima@utk.edu).

[‡]Department of Economics, Federal University of Paraiba-Brazil.

[‡]Department of Economics, University of Tennessee at Knoxville, 527A Stokely Management Center and NBER.

from land-poor households. Similar findings in other developing countries are reported by Kambahampati and Rajan (2006), Dumas (2007) and Kruger (2007).

In the presence of illiquidity in land markets, land wealth differs from wealth in general. In particular, as land wealth rises there are two offsetting forces affecting the child labor decision. On one hand, increases in wealth encourage the consumption of "normal" goods, including child leisure and schooling, through an income effect. This is a generalization of Basu and Van's luxury axiom. On the other hand, because the wealth comes in the form of workable land, the opportunity cost of leisure rises as well. Thus there is a substitution effect whereby the increase in land wealth encourages *more* work.

In a recent paper, Fan (2011) develops a model in which the preference of a family affects its decision to send a child to the labor market. The greater the parents' taste for children's leisure, the stronger the income effect and the less likely parents are to send children to work. Because such "altruism" cannot be directly observed, the conditional distribution of child labor will exhibit great dispersion. This dispersion, in turn, motivates quantile regression to separate the mean effect (where a wealth paradox exists) from the effect of household wealth on child labor at various points of the child labor distribution. Quantile regression allows us to pinpoint whether substitution or income effects are greater across the child labor distribution and, under the assumption that *conditional* quantiles of the child labor distribution reflect differences in household preferences, attribute the "wealth paradox" to parents with particular preferences. This technique has been critical to identification in other settings with heterogeneous agents, *inter alia* the impact of welfare reform on earnings (Bitler, Gelbach and Hoynes, 2006), returns to education (Arias, Hallock and Sosa-Escudero, 2001) and birthweight determinants (Abrevaya and Dahl, 2008).

Our results suggest that, for both boys and girls, the effect of land size (a proxy for wealth) on child labor is negative among children who are initially exposed to a small workload (lower quantiles of the child labor distribution) and positive on those with a high workload (upper quantiles). Because these wealth effects by quantile are conditioned on household expenditures per capita and other household observables, they do not reflect simple differences in household income or consumption across conditional quantiles. Thus we interpret the mean effect "wealth paradox" as a manifestation of the behavior of a subset of non-altruistic parents.

2 Econometric Methodology

We estimate the relationship between wealth, measured by the size of the farm, and child labor supply, measured by the hours of work of children in family agricultural activities. Three econometric issues in the data must be addressed. First, the data display heteroskedasticity. Second, the data contain many child labor observations equal to zero, censoring that reflects the choice not to send children to the labor market at all. Finally, we wish to establish the relationship between wealth and child labor net of household income. Our proxy for income will be per capita household expenditures, but household expenditure and child labor supply decisions are made simultaneously by the families and, therefore, expenditures are endogenous in the regression equation. Bhalotra and Heady (2003) partially address these identification issues by considering a censored regression model estimated with a control variable approach developed by Smith and Blundell (1986) to deal with endogeneity. Their approach does not address heteroskedasticity and, more critically, quantile functions which we argue are critical for identifying heterogeneous effects.

We address all of these issues by extending the Bhalotra and Heady (2003) approach towards quantile regression utilizing the Censored Quantile Instrumental Variable (CQIV) developed by Chernozhukov, Fernández-Val and Kowalski (2011). This technique combines semiparametric censored quantile regression, developed by Powell (1986), with a control variable approach to allow the incorporation of endogenous regressors. Classical linear normality and homoscedasticity assumptions are not required. More details are available in Chernozhukov *et al.* (2011) and in the online appendix to this paper.[1] To facilitate comparison, we use the same data for Pakistan as in Bhalotra and Heady (2003), and our model specifications replicate theirs exactly. Like others before us, we assume land wealth to be exogenous as land is usually inherited and the market for land in developing countries is highly illiquid.[2]

Setting aside the censoring problem for now, the equation for hours of child labor (H) is:

$$\begin{aligned} H_i &= W_i\beta + D_i\gamma + e_i \qquad (1) \\ i &= 1, ..., N \qquad (2) \end{aligned}$$

where (Z) is a vector of exogenous variables, (X) is an endogenous variable and N is the sample size. The quantile function of H conditional on the observables Z and X would be given by

$$Q_\tau\left(H|Z,X\right) = Z\beta\left(\tau\right) + X\gamma\left(\tau\right) \qquad (3)$$

where $\tau \in (0, 1)$. The advantage of this technique over a standard regression procedure used elsewhere in the literature is that it allows a characterization of the conditional distribution of the dependent variable as a function of covariates. Since hours of work for children from non-altruistic families are likely above median, we could estimate the third quartile, $Q_{0.75}\left(H|Z,X\right)$, to identify the wealth effect on those children. Likewise, the wealth effect on children from altruistic parents could be captured by estimating the first quartile, $Q_{0.25}\left(H|Z,X\right)$. For this reason, quantile regression can be a powerful tool to study the wealth effect on child labor across family preferences.

Estimation of (1) needs to account for all three identification issues previously discussed. The two-step CQIV estimator first expresses the endogenous variable X (per capita household expenditures) in terms of exogenous variables. As in Bhalotra and Heady (2003), these exogenous variables include the community unemployment rate together with indicators of the level of infrastructure development of the community, namely, the presence of railway, market and piped water. Interactions of these variables with the education of the head of

[1] Available at `http://web.utk.edu/~mwanamak/ChildLabor_Appendix.pdf`

[2] See Swain (2001) and Rosenzweig and Wolpin (1985).

household are also included in order not to lose the effect of variation in income within communities. We estimate the first stage using standard quantile regression.

In the second stage, we add the control variable obtained from the first stage to equation (1) and then estimate it by using the MCMC-simulated censored quantile regression (Chernozhukov and Hong, 2003), which is a computationally attractive method to optimize the Powell (1986) objective function. Additional details can be found in the Online Appendix, where we also show that controlling for endogeneity is critical for unbiased inference.

3 Data and Empirical Results

The data for this study are from the Pakistan Integrated Household Survey (PIHS) 1991.[3] Each household represents a unit of observation, and the dependent variable of interest is the number of child hours worked within the household's reference week. The wealth effect of interest is captured using the size of agricultural land in acres (and its quadratic term) as a proxy for wealth. Following Bhalotra and Heady (2003), we utilize household food expenditure per capita (using a control variable approach to control for endogeneity, as discussed above) and the education level of each parent to control for income and household resources. A full list of covariates and their average value is contained in the Online Appendix.

The results of Bhalotra and Heady (2003) indicate that farm size has a positive effect on child labor, although the effect of this variable is statistically significant only in the case of girls. We estimate the same functional form using quantile regression techniques as described in Section 2 and report marginal effects for the land wealth variables in Table 1.[4]

Our results indicate that households respond differently to increases in land wealth, with statistically significant results for both boys and girls. For households where children already work a small number of hours conditional on observables ($\tau = 0.25$ and $\tau = 0.5$), the income effect dominates and increases in land ownership reduce the amount of time children participate in farm work. The result is statistically significant. We label these households "altruistic", although we acknowledge that there are other unobservable characteristics of households that might lead to a lower level of (conditional) child labor.

In contrast, for "non-altruistic" families where children already work many hours a day, the substitution effect dominates ($\tau = 0.75$). Coefficients on land are positive and significant for both boys and girls, while coefficients on land squared are negative. Practically, increases in land result in reduced child labor for these households only when land is greater than 10.58 acres for boys and 54.96 acres for girls, corresponding to the >75th and >90th quantiles of the land distribution, respectively. Thus, only at very high levels of wealth does the income effect overtake the substitution effect for these households. There are a number of potential

[3] This survey was done by the government of Pakistan in cooperation with the World Bank as part of the series of the Living Standards Measurement Research Study (LSMS) in developing countries.

[4] Estimated coefficients and the empirical analysis for the remaining control variables are available in the Online Appendix.

explanations for this result, including the possibility that the children of these households have experience on the farm that makes them more productive compared to new employees. As a result, child labor is more attractive for these families than available alternatives, and the wealth paradox holds. The observation that households appear to be more altruistic towards male children echoes other results in the literature.

Thus, our quantile regression method allows us to identify an empirical relation between the wealth paradox and family preferences, complementing the theoretical analysis initiated by Fan (2011). Households with high initial levels of child labor account for the entirety of the wealth paradox documented at the mean in Bhalotra and Heady (2003) and, perhaps, in other empirical studies.

4 Concluding Remarks

Fan (2011) showed that the greater is parent's taste for children's leisure, the less likely parents are to send their children to work. We took this result as motivation to introduce quantile regression techniques to the literature of child labor. Our method accounts for all the important statistical issues found in the data, which includes a large amount of observations equal to zero, heteroskedasticity and endogeneity. Our results suggest that the luxury axiom can be used to explain child labor when families are altruistic, but the wealth paradox holds among non-altruistic families. Thus, public policies aimed at eliminating child labor should recognize the existence of heterogeneity in family preferences.

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Table 1: Quantile regression model coefficients: child work on the household farm.

	Boys			Girls		
	tau 0.25	tau 0.50	tau 0.75	tau 0.25	tau 0.50	tau 0.75
Land	-1.887^{*}	-2.262^{***}	0.197^{**}	-0.302	-1.297^{***}	0.143^{***}
	(0.977)	(0.766)	(0.095)	(0.531)	(0.501)	(0.030)
Land Squared	-3.285^{***}	-2.971^{***}	-0.009^{**}	-3.361^{***}	-4.235^{**}	-0.001^{***}
	(1.153)	(0.995)	(0.004)	(0.950)	(2.047)	(0.000)

Notes: Coefficients estimated via censored quantile regression using model spefication and data described in the text.

(*), (**), (***) denote statistically significant at 10%, 5% and 1% respectively. Standard errors in parenthesis