7-2014

Child Labor, the Wealth Paradox, and Common Forest Management in Bolivia

Randall Bluffstone

Citation Details

Bluffstone, Randy. Child Labor, the Wealth Paradox, and Common Forest Management in Bolivia. No. edf-dp-14-16. 2014.

Environment for Development

Discussion Paper Series July 2014 ■ EfD DP 14-16

Child Labor, the Wealth Paradox, and Common Forest Management in Bolivia

Randall Bluffstone

Sida

EfD Environment for Development

RESOURCES FOR THE FUTURE

Environment for Development Centers

Central America
Research Program in Economics and Environment for Development in Central America
Tropical Agricultural Research and Higher Education Center (CATIE)
Email: centralamerica@efdinitiative.org

Chile
Research Nucleus on Environmental and Natural Resource Economics (NENRE)
Universidad de Concepción
Email: chile@efdinitiative.org

China
Environmental Economics Program in China (EEPC)
Peking University
Email: china@efdinitiative.org

Ethiopia
Environmental Economics Policy Forum for Ethiopia (EEPFE)
Ethiopian Development Research Institute (EDRI/AAU)
Email: ethiopia@efdinitiative.org

Kenya
Environment for Development Kenya
University of Nairobi with
Kenya Institute for Public Policy Research and Analysis (KIPPRA)
Email: kenya@efdinitiative.org

South Africa
Environmental Economics Policy Research Unit (EPRU)
University of Cape Town
Email: southafrica@efdinitiative.org

Sweden
Environmental Economics Unit
University of Gothenburg

Email: info@efdinitiative.org

Tanzania
Environment for Development Tanzania
University of Dar es Salaam
Email: tanzania@efdinitiative.org

USA (Washington, DC)
Resources for the Future (RFF)
Email: usa@efdintiative.org

The Environment for Development (EfD) initiative is an environmental economics program focused on international research collaboration, policy advice, and academic training. Financial support is provided by the Swedish International Development Cooperation Agency (Sida). Learn more at www.efdinitiative.org or contact info@efdinitiative.org.

Child Labor, the Wealth Paradox, and Common Forest Management in Bolivia

Randall Bluffstone

Abstract

That wealthier developing country households may rely more heavily on child labor than poorer households has come to be known as the "wealth paradox." This paper tests for a wealth paradox with regard to common natural resource wealth by analyzing the relationship between child labor and improved common property forest management (CPFM) in Bolivia. Data are analyzed using several econometric methods and it is found that households experiencing more effective CPFM generally use more forest-based and total child labor. The analysis also confirms others' findings of a private wealth paradox with regard to private land and extends the analysis to evaluate the effect of ownership of animals.

Key Words: forests, common property, Bolivia, child labor

JEL Codes: Q23, Q56

Contents

Child Labor, the Wealth Paradox, and Common Forest Management in Bolivia

Randall Bluffstone*

1. Introduction

We know that children are important sources of labor in developing countries. The International Labour Organization estimates that in 2004 approximately 314 million children were engaged in work and 218 million did so in ways that contravened international conventions. These children provide a variety of services, including helping in the home, weeding farm plots, grazing animals, performing wage labor and cutting fuelwood and fodder (Basu and Van 1998; Basu et al. 2010; Kohlin and Amacher 2005; Cooke et al. 2008; Edmonds and Turk 2002; Grootaert and Kanbur 1995). Empirically, most child workers are in Asia and Sub-Saharan Africa, but child labor is important throughout the developing world and is believed to be rising in Latin America and Sub-Saharan Africa. In many low income countries, child labor force participation is above 40% (Hagemann et al. 2006; Basu 1999).

The linkage between child labor and forest management is of interest, because most activities done by children in developing countries – and, for that matter, by adults – are complemented by land. Indeed, it is observed that in many developing countries farming households with more agricultural land – the most important store of wealth in the developing world – often also use more child labor. That richer households may rely more heavily on their children's labor than poorer households has come to be known as the wealth paradox (Bhalotra and Heady 2003). A "paradox" exists, because as Basu and Van (1998) and other authors (e.g., Edmonds 2005; Bhalotra 2007) have shown, typically, as wealth and incomes increase, child labor declines.

* Department of Economics, Portland State University, P.O. Box 751, Portland, OR 97207-0751, Ph: 503-725-3938, Fax: 503-725-3945, Email: bluffsto@pdx.edu.

Acknowledgements: The author would like to thank Ed Barbier and Eric Edmonds for their generosity and helpful comments on earlier versions, the AVINA Foundation for financial support and Incuestas y Estudios for conducting the household survey. He is also grateful to Ramiro Molina, Marco Boscolo, Ricardo Godoy, and Menale Kassie for helpful insights, and to Oregon State University and Oregon Resource and Environmental Economics Workshop participants for helpful comments. Thanks are also due to the Social Sustainability Workshop at Portland State University for additional financial support and Ecotrust Northwest for hosting me during the paper's revision.

What concerns us here is that farming systems tend to be integrated with common natural resources, such as forests and pasture lands, and over 1.6 billion people depend on forests for a significant portion of their livelihoods (http://www.fao.org/forestry/28811/en/). Households depend on these common resources for fuels, animal food, building materials, fruits and medicines, but household labor is almost always necessary to access these valuable resources. The nature and source of those labor inputs therefore becomes an interesting topic, particularly as forest management improves and natural resource quality and value increase.

The focus of this paper is on the relationship between commonly owned forests – a particular form of wealth that happens to be held by communities – and child labor. In the remainder of the paper, I estimate the effect of what is generally considered more stringent common property forest management (CPFM) on two types of child labor while accounting for a variety of econometric issues. The paper extends the empirical literature on the economics of forestry to consider effects on child labor and also adds to the literature on child labor in developing countries by extending the notion of the child labor wealth paradox to include commonly held wealth such as forest resources.

To better understand past work, the remainder of this section discusses the key child labor and common property literature. Section 2 then presents data from the Bolivian Andes that are used to analyze the relationship between CPFM and child labor. Section 3 discusses the empirical approach and Section 4 the results. The final section evaluates implications and concludes.

The services provided by children are widely regarded as important for households involved in very labor-intensive production systems and some have even suggested that household labor requirements at least partially explain high fertility rates (Filmer and Pritchett 2002; Dasgupta 2000; Perkins et al. 2001). In attempting to explain the existence and persistence of child labor, recent economic literature has suggested that significant attention should be given to constraints facing poor households in rural areas of developing countries (e.g., Grootaert and Kanbur 1995). This literature builds on the seminal theoretical paper by Basu and Van (1998) and suggests that poor households in rural areas – particularly if households are unable to meet basic needs without child labor – are much more likely to use child labor (Edmonds and Turk 2002; Bhalotra 2007).

But many authors have also found wealth and income paradoxes. Bhalotra and Heady (2003) find that in Ghana and Pakistan households with more agricultural land also use more female child labor. Similar results are derived for Burkina Faso by Dumas (2007) and for

Ethiopia by Cockburn and Dostie (2007), who point out that in rural Ethiopia exploiting wealth nearly always requires labor. These and other authors cite lack of labor, credit and insurance markets as reasons households turn to children rather than hiring in labor.

I would like to note that markets for key agricultural production inputs are also missing. For example, access to forest products like timber, fuelwood, fodder and grazing rights are typically imperfect or non-existent and therefore households generally produce and consume these goods themselves. Households often access these inputs through communal arrangements and it is here, as pointed out by Dasgupta (2000), Filmer and Pritchett (2002) and others, that we observe market failures that may distort forest labor supply.

In recent decades, there have been important advances in our understanding of common natural resources and what is required to increase direct use values from them. A large literature has emerged that, for example, emphasizes the distinction between open access – where resources are not owned and access is free – and community ownership, where the resources are owned but ownership is in common. The theoretical literature has largely found that communities can coordinate effectively as long as incentives to cooperate exist (e.g., Olson 1965; Dayton-Johnson 2000; Ostrom 1990; Bromley 1990; Baland and Platteau 1996; Sethi and Somanathan 1996).

Over time, almost a conventional wisdom advocating devolution of natural resources has emerged and many countries have legislated local-level management. Agrawal (2001; 2000) notes that more than 50 countries have ceded some control over natural resources. For example, devolution of forests has been underway in Nepal since the early 1980s and most forest lands were transferred to users in 1993 through the creation of forest user groups (Adhikari 2002; Cooke 2000; Pradhan and Parks 1995). Tanzania, Ethiopia and Kenya all have taken legislative steps toward forest devolution (Mekonnen and Bluffstone 2007). In Bolivia, which is the focus of this paper, communities have had control over many natural resources at least since 1952.

In addition to devolution itself, certain policies are now regarded as best practices. These include institutional characteristics such as more public participation and democracy, fair allocation of forest resources and clear criteria for accessing resources. Management tools include clear rules for extracting resources, effective monitoring by villagers and officials, reasonable graduated sanctioning of transgressors and, if appropriate, payments for products (Ostrom 1990; Agrawal 2000; 2001).

As has been discussed by a variety of authors, a number of effects can be expected from more effective CPFM (Adhikari 2002; Bluffstone et al. 2008; Kohlin and Amacher 2005; Linde-

Rahr 2003; Nepal et al. 2007). For example, Nepal et al. (2007) and Bluffstone et al. (2008) found that effective CPFM institutions spur on-farm tree planting. Adhikari (2002), however, raises concerns about equity effects in Nepal. With the exception of Kohlin and Amacher (2005), however, for whom child labor is not a central issue, I am not aware of any literature that examines the links between CPFM and child labor.

2. Data and Descriptive Statistics

We now turn to the data used to test whether more effective CPFM affects child labor and therefore offers evidence related to a potential common wealth paradox. Data come from an April 2000 survey of village officials and 378 households in 32 communities in the five Bolivian Andes departments of Cochabamba, Chuquisaca, Oruro, Potosi and La Paz. Surveys were conducted at the end of the summer rainy season when weather does not limit labor choices. The sample is stratified to include more villages and households in the more populated departments of Cochabamba, Potosi and La Paz (25% each) and about half this amount from Oruro and Chuquisaca.

The household survey asks about 1) household characteristics; 2) forest management; 3) consumption; 4) production; and 5) assets. Average household size is 3.8 members and 66% of households have children, with a mean of 2.6. Eighty-seven percent of respondents primarily earn their livelihoods by farming. The village level survey includes information on village total, agricultural and grazing land area, ethnicities, institutions (e.g., land management, forestry), population and settlement patterns, with the primary purpose to offer instruments for IV analysis.

In the Andes, average elevation is higher in the north (by about 500 m), but so are temperature and rainfall. Spanish colonization was concentrated in the north, which had a culture of private property earlier than other areas (Castro and Rist 1999; Moscoso and Villanueva 1997). A variety of institutional regimes control natural resources in rural Bolivia. In contrast to the lowlands, highland forests have limited commercial value and have largely escaped central government control. In most areas, CPFM systems have therefore evolved locally – perhaps over centuries – with significant and idiosyncratic differences across communities. Our village survey suggests that, in some areas, there is de facto open access, with effectively no management. In the remainder, though, a variety of officials and locally developed, custom-based, often subtle structures regulate forests. For example, in some areas there are no official managers and residents agree on rules for forest use in village meetings. Others have officials involved, including mayors, council members, community directors and presidents, peasant union presidents, forestry directors and heads of committees for environmental protection.

Thirty-three percent of villages regulate forests based on formal laws, but all those also use customary rules. In total, 78% of villages regulate forests by custom and 22% have no regulation at all. Except for grazing and timber, few villages control extraction. For example, while 55% of villages regulate timber and one-third control grazing, less than 10% restrict fuelwood and fodder collections.

Table 1 presents key descriptive statistics on household labor across six key activities during the week before the survey was conducted. We see that households work long hours on average. With an average of 3.8 members per household, 1.45 of them children, covering an average workload of 137 hours per week is likely to be a challenge. The most labor-intensive activity is agriculture, followed by household work and grazing.

Table 2 breaks these labor shares down by age, but, because of lack of data, not by gender. Child labor is clearly an important, but not dominant, component of household labor, with 65% of households reporting no child labor. Among those with children, about half say they use some child labor. The 36 to 65 age group works most, followed by 16 to 35 year olds.

Children, on average, supply about 9% of household labor, but do not contribute equally to all activities. They are especially active in household work (4.2 hours per week or 13% of total) and grazing (4.3 hours or 16% of total) and it is only for these categories that they provide more input than the elderly. Agriculture is significant (2.5 hours per week on average), but child labor is small relative to all other age groups. Fuel and fodder collection, which are small users of household labor, absorb virtually no children’s time and those 36 to 65 contribute most to fuelwood collection, which is physically demanding. No children participate in wage labor.

Many households use no child labor, but, where it exists, I find that Bolivian parents allocate children tasks that are not too physically demanding, but absorb a lot of time. (Filmer and Pritchett (2002) find the same in Pakistan.) Though by no means concentrated in forest-intensive activities, grazing is certainly one of the most important tasks.

To estimate the effect of more stringent CPFM on child labor, I create CPFM indices based on criteria for well-functioning common property, as suggested by Ostrom (1990) and Agrawal (2001). Nine indices are created for each household using the formula in (1), which is used by UNDP to compute the human development index and is [0,1]. A_{ij} is the value of index component i for household j and Min_i and Max_i are the sample minimum and maximum for component i. CPFM variable definitions, means and standard deviations are presented in Table 3. At the top is the CPFM index, which is an average of institutional characteristics and management tools indices, which are themselves averages of specialized indices. All components are weighted equally.

$$(1)\ Index_{ij} = \sum_{i=1}^{k} (A_{ij} - Min_i)/(Max_i - Min_i)$$

Our CPFM indices are based on respondent perceptions. Perceptions are used for two reasons. First, in developing countries, on-the-ground management can often correspond poorly with stated policies. Perceptions therefore have the potential to better reflect reality. Second, "objective" measures of CPFM require interviews with village leaders or forest managers who might have difficulties characterizing the details of CPFM facing households. Perceptions therefore offer a better way to analyze detailed CPFM components.

Table 3 indicates rather loose management. Mean overall CPFM index is only 0.31 and the mean of the management tools index is only 0.13. The institutional characteristics index mean is 0.45, but the mean clarity index is only 0.23 and participation/democracy 0.09. In fact, only 28% say that forest access rules are at least "somewhat clear." Yet, despite few formal controls and apparent alienation, a substantial minority reports that officials and villagers monitor forests. Data also suggest that villagers are motivated by social pressures. Almost half say others would at least "probably" be unhappy or angry if they took too much fuelwood or fodder. A similar proportion would be embarrassed and many said they could lose privileges.

The institutional characteristics and management tools sub-indices appear to be measuring different CPFM features, because they are very weakly correlated with each other ($\rho = 0.13$). We are therefore not concerned about multicollinearity between the sub-indices.[1] CPFM varies across departments. The overall CPFM index is positively correlated with the Cochabamba ($\rho = 0.32$), La Paz ($\rho = 0.24$) and Chuquisaca ($\rho = 0.19$) dummies, but negatively correlated with Potosi ($\rho = -0.52$) and Oruro ($\rho = -0.27$). Management tools are positively associated with La Paz ($\rho = 0.42$), but in Cochabamba and Chuquisaca institutional characteristics dominate ($\rho = 0.41$) and management tools are negatively associated ($\rho = -0.07$).

We do not have detailed qualitative information on the nature of CPFM in our 32 study communities and cannot shed much light on the reasons for regional differences. As shown in the

[1] We also examine correlation coefficients between the more detailed CPFM indices. Other than a high correlation between formal penalties and social sanctions ($\rho = 0.74$), and modest correlations between the participation/democracy index and four management tools variables, there do not appear to be serious worries about multicollinearity. These findings are available from the author.

next section, however, villages in departments with higher levels of CPFM tend to have a greater area, be predominantly of the Aymara rather than Quechua ethnic group, and have management regulated by custom.

3. Empirical Approach

The empirical approach is to estimate structural models of total and environmental child labor, where models allow for the possibility that CPFM, household fertility and fuelwood use are endogenous. I also estimate treatment effects models based on nearest neighbor propensity score matching as an alternative to explicitly modeling endogeneity.

This multi-faceted approach is taken because, as Heckman (2010) has emphasized, explicit structural models can offer important policy insights, but estimation is often difficult. On the other hand, treatment effects models are expeditious, but typically mask key economic relationships. He advocates placing economic questions and theory "front and center" in these analyses and combining econometric techniques as appropriate.

Child labor variables are defined in two ways to derive estimates that are robust to dependent variable definition and econometric technique. Environmental child labor includes fuelwood collection, grazing and fodder collection, while total labor adds household work and agricultural labor. These are analyzed both as binomials, indicating whether households used any child labor during the week before the survey, and as total hours of child labor.

Descriptive statistics are given in Tables 4 and 5. Environmental labor on average represents roughly half of total child labor, but the variance is much larger than for total labor. Mean total child labor is about 12 hours per week and 5.37 for environmental labor. About 35% of households use child labor and 22% environmental child labor. Censoring at zero is therefore an important data issue.

A final refinement is that I examine both the full sample and the sub-sample of households with children. The full sample is analyzed, because it allows me to adjust for and examine any linkages between child labor and fertility; without including those households that for whatever reason do not have children, incorporating fertility decisions is not possible.

In sum, binomial regression, continuous regression and treatment effects models of environmental and total child labor are each estimated for the full sample and for households with children. These estimates are done separately for the overall CPFM index and its two sub-indices. Because many households do not use child labor, we should be wary that decision processes involve sample selection (Heckman 1979; Linde-Rahr 2003). I test for sample selection, but I do not find the inverse Mills ratio remotely significant in any model (p value 0.63 to 0.75). I therefore do not report Heckman results, though they are available upon request.

Without sample selection, the standard method when data are left-censored is to use Tobit, but this is correct only if the household's decision-making process for deciding whether to use child labor is the same as for choosing hours of labor. I test this restriction by comparing the Tobit with the model of Cragg (1971), which utilizes a Probit for the first stage followed by a truncated regression model. Using likelihood ratio tests, I reject the Tobit as too restrictive at better than the 1% level (likelihood ratio $\chi^2 = 89.23$, prob. $> \chi^2 = 0.00$). I therefore present Probit first-hurdle results followed by second-hurdle truncated regressions with errors bootstrapped (1000 replications) (Guann 2003).[2] Before presenting the double-hurdle model, 2SLS IV regression results are discussed.

Our independent variables of interest are the overall common property (top of Table 3), institutional characteristics and management tools indices (second row of Table 3). Results on lower-level indices are available from the author, but are not reported in order to focus this discussion.

The literature has debated the degree to which child labor and fertility decisions are linked (e.g., Dasgupta 2000; Filmer and Pritchett 2002). I therefore include children not only as a covariate, but as a variable of interest. I also attempt to disentangle the effects of forest extractions from the effects of more developed CPFM on child labor. Households cook exclusively with biomass, and fuelwood is preferred; therefore, use of more fuelwood indicates, *ceteris paribus,* that households get more of their preferred product. I therefore include total fuelwood use during the week prior to the survey as an independent variable.

Independent variables of primary interest are potentially endogenous. I do not assume endogeneity, however, but test for it using Durbin and Wu-Hausman tests and find that we can reject exogeneity in the 2SLS model for the full sample at the 5% level at least.[4] The model estimated is a separable rather than a non-separable model, as was estimated, for example, by Linde-Rahr (2003) and Cooke (1998; 2000). In the literature, the marginal product in agriculture is often used as a shadow value (Singh et al. 1986), but, as shown in Table 1, such an assumption would not be appropriate.

---

[2] Predicted values come from the regression models presented in Table 6. Truncated regression is applied only to those observations with non-zero values of the dependent variable.

Table 5 presents descriptive statistics for covariates and excluded exogenous variables, along with expected signs and the reasons for including them. The table indicates that, though generally poor, most households are integrated with markets, with 73% having gone to a store during the previous week. This is despite a mean travel time of two hours. Borrowing is difficult, with only 16% of respondents having access to credit from local moneylenders. Mean land holdings are 1.47 hectares and 10% of households are landless. The values are similar to the means for extremely poor households (income < $1/day/person) in a variety of countries analyzed by Banerjee and Duflo (2007). Ownership of large animals are limited, with less than half reporting that they have cows. Over 50% have sheep, with a mean of nine.

The excluded instruments presented in Table 5 identify the first stage equations when tests suggest that CPFM indices, children or fuelwood use are endogenous. These instruments are chosen because they are highly correlated with CPFM indices, fertility and fuelwood use and are believed to affect village norms. They are also theoretically and empirically unrelated to child labor. For example, the mean and median Spearman correlations between excluded exogenous variables and total child labor are 0.17. Rationales for choosing these variables as excluded exogenous variables are discussed in Table 5. As discussed in the next section, we test the power of our instruments and find that have sufficient power. Data are from household and village leader surveys.

Villages have a mean of 535 households, are primarily Quechua, are evenly split between clustered and disbursed settlement patterns and generally have clear boundaries. About half have regulations for timber cutting and allow people to sell their land. Typically, though, forest management is determined wholly by custom, though some villages also utilize formal laws.

The IV models are all over-identified. I therefore test over-identification restrictions using Sargan and Basmann methods and confirm that all pass these tests. Weak instruments are tested using Shea's partial R^2. All test results are reported with relevant IV regression results.

The treatment effects models estimate the average treatment effect on the treated (ATT) using nearest neighbor propensity score matching.[5] "Treatment" in these models indicates that households experience CPFM greater than the median value of the relevant CPFM measure

[5] In all models, the propensity score specification satisfies the balancing property.

(overall CPFM, institutional characteristics, management tools). Propensity scores are estimated using the excluded exogenous variables in Table 5 and ATTs are estimated with all exogenous covariates as right side variables.

As noted by Heckman (2010) and Kassie et al. (2008), standard regression analysis assumes truly comparable treated and untreated households. Propensity score matching helps assure this comparability and constructs a counterfactual that examines the effects on the treated had they gone untreated and vice versa. Estimates using matched samples also reduce endogeneity bias.

4. Results

I begin by briefly discussing first-stage CPFM index, fertility and fuelwood collection models. I then present 2SLS and Probit models of total and environmental child labor for the full sample and sub-sample with children. Sample sizes reflect the need for full-rank matrices and are less than 378 in all models.

As shown in Table 6, a number of variables are associated with children, CPFM indices and fuelwood collections and, based on F tests, all models are significant at better than the 1% level. Adjusted R^2 values are all higher than 0.33 and as high as 0.85 for children. These results suggest that weak instruments may not be a problem. No variable is significant in all models, though we find that respondents have systematically lower values of all CPFM indices where timber cutting is regulated.

The determinants of fertility are perhaps of most interest. I find that households with electricity *have on average one fewer child than those without those services* ($p \approx 0.000$). More educated households have fewer children, as do households with more sheep. The results therefore confirm results of others (e.g., Dasgupta 2000) that providing infrastructure and education reduces fertility.

Table 7 presents 2SLS IV results for total and environmental labor for the full and sub-sample of households with children. All models have substantial explanatory power, with Wald tests significant at $p>0.000$. In models using the full sample, I reject exogeneity of potentially endogenous variables, at least at the 10% significance level, and, depending on whether Wu Hausman F or Durban χ^2 tests are used, at better than the 1% level in some models. For the sub-sample of households with children, we cannot reject exogeneity in any model, suggesting that OLS is a better technique. OLS results are similar to those from IV; in the interest of brevity, I refer to them but do not present them. OLS results are available from the author.

That exogeneity cannot be rejected for households with children suggests that, while CPFM measures, children and fuelwood use are endogenous to households' child labor decisions, because they are bound up with choices related to *whether* households have children. For example, child labor affects fuelwood collections (not only vice-versa) only as part of households' decisions whether to have children.

I test for weak instruments using Shea's partial R^2 and find, as shown in Table 7, that the instruments chosen are strong. That the value of Shea's partial R^2 is typically greater than 0.30, and often over 0.40, suggests substantial explanatory power of the excluded variables (Cameron and Trivedi 2005). I test the over-identifying restrictions using Sargan and Basmann tests and find that, for the full sample (where exogeneity can be rejected), 15 of the 16 models pass over-identifying restrictions tests.

I find that the effect of the overall CPFM index on child labor is positive and, for environmental child labor, is significantly different from zero with an elastic response (ε =1.13). In the OLS models not presented (i.e., for households with children), overall CPFM is positively correlated with environmental and total child labor and significant at better than the 5% significance level with elasticities of 0.32 to 0.45.

Dividing CPFM into sub-indices, I find CPFM has very statistically significant effects on child labor. The institutional characteristics sub-index is correlated with more total and environmental child labor in all models for both the full and child-only samples (also true for OLS models with ε =1.1 and 1.28) and management tools are associated with less child labor. Marginal effects for the full sample are high, yielding elasticities of the institutional characteristics index relative to total child labor of 1.20 and environmental child labor of 1.9. Elasticities of management tools with respect to child labor are -0.65 to -0.80, which suggests these CPFM components pull in opposite directions.

All models in Table 7 indicate that fertility affects child labor decisions, with more children (instrumented due to endogeneity) correlated with more total and environmental child labor. The response is elastic ($\varepsilon \approx 1.1$) in models of total child labor and slightly inelastic ($\varepsilon \approx 0.86$) for environmental child labor; households therefore make child labor decisions based on their fertility choices and, because children are endogenous to the child labor decision, child labor requirements also affect fertility.

Fuelwood use is positively correlated with child labor, with elasticities in the 0.40 to 0.50 range. This finding indicates that more and better quality fuels are associated with the use of child labor; from a fuel quality and use perspective, given common access to fuelwood, child labor and household welfare appear to go hand-in-hand. Because fuelwood collections are endogenous to the child labor decision, child labor also affects fuelwood collections.

Relatively few covariates yield consistent results across samples and definitions of child labor. An exception is electricity, to some extent. The *availability of electricity is associated with reduced environmental child labor in most models, which suggests electricity substitutes for household labor in ways that benefit children*. As was previously discussed, the existence of electricity is also correlated with lower fertility.

Among households with children, more educated households use less child labor and this finding is significant in some IV models and at least at the 10% level in OLS models. As shown by the positive and sometimes significant coefficient estimates on wealth variables (e.g., land, cattle and sheep), there is some evidence that wealthier households use more child labor.

Table 8 presents Probit results for total and environmental labor. This is the first stage of the Cragg (1971) double-hurdle model. I test for exogeneity of the potentially endogenous variables and reject exogeneity for environmental child labor, but not for total labor. I find, though, that IV Probit models of environmental labor cannot return marginal effects. I therefore report Probit results. IV Probit findings are available and similar to Probit models.

Probit results are comparable to those from the 2SLS models. Overall CPFM and institutional characteristics are positively associated with child labor and in three models (total child labor using CPFM sub-indices) statistically significant, with elasticities of 0.78 (full sample) and 0.38 (sub-sample with children). Management tools are again negatively associated with child labor and are statistically significant for total child labor. Elasticities are -0.28 and -0.15. Number of children are positively associated with the existence of child labor ($\varepsilon \approx 1.0$) and are significant in all models. Fuelwood use is also positively related to child labor in all models, confirming that more fuelwood is associated with the use of child labor; all else equal, households using more and better fuels require more labor – including children.

Relatively few covariates stand out as especially related to the existence of child labor, though the use of tractors, and in some models, key wealth variables such as land, cattle and sheep, are positively correlated and statistically significant. Other variables, for example those related to market integration, are not significant.

Table 9 presents truncated regression results, which is the second hurdle of the Cragg (1971) model. CPFM coefficient estimates are consistent with previous models. Overall CPFM and institutional characteristics indices are positively correlated with child labor, while management tools are negatively correlated with child labor for households that use any child labor. In the full sample, no CPFM estimates are statistically significant, but management tools are significant in the sub-sample. In contrast to other models, number of children are significantly – but negatively – associated with child labor. This suggests that fertility indeed affects child labor choices, but once we break the child labor decision into binary and continuous parts, we find that fertility is positively associated with the *existence* of child labor, but negatively associated with the *amount* of labor. Elasticities for the second hurdle are estimated to be quite high ($\varepsilon \approx -3.8$), suggesting that households with more children are more likely to have child labor, but more children does not imply more child labor; indeed, the opposite is indicated.

Fuelwood use is again positively related to child labor, but is not significant, in contrast to all but a few previous models. This finding perhaps suggests that more and better quality fuels are associated with the *existence* of child labor, but not the *amount*. Among covariates, we see some key differences with the first hurdle. First, the number of females is positively correlated and statistically significant in all models. For total child labor, the use of tractors tends to reduce child labor as does the number of trips to stores (a key measure of market integration). With the exception of numbers of sheep – which require daily grazing – other measures of wealth are not correlated with child labor.

I now cross-check these regression results with non-parametric treatment effects models using matched samples based on nearest neighbor propensity score matching. Table 10 reports ATTs that measure the average effect on child labor of CPFM indices above the median. For the full sample in all but one model, overall CPFM and institutional characteristics indices positively affect total and environmental child labor and these estimates are generally statistically significant at better than the 1% level. Average effects are also empirically large. For example, if households experience above-median levels of these CPFM variables, the average effect is to *more than double child labor*. There is also more than *a 50% increase in the probability that households use any child labor*. ATTs are not significant in models using the sub-sample of households with children and, consistent with some other models, management tool ATT estimates are not significant.

In sum, based on four estimation techniques I conclude that more stringent overall CPFM generally increases environmental and total child labor in the Bolivian Andes. This conclusion is robust to model specification and choice of sample. *In no model is the estimated effect of overall CPFM on child labor negative and in most cases positive estimated coefficients are statistically significant*. These findings also hold for the institutional characteristics sub-index; indeed, a positive and statistically significant correlation between the institutional characteristics sub-index and child labor is one of the most robust findings. Management tools clearly pull in the opposite direction, however, with better management tools reducing child labor.

5. Conclusions

This paper examined the so-called wealth paradox with respect to common wealth. We do not have data on forest quality and are therefore not able to directly examine common forest wealth effects, but instead focus directly on forest management, which has its own appeal. The literature on the meaning and effects of more effective CPFM is indeed clear enough, however, that, *ceteris paribus*, it is hard to imagine households experiencing what we think of as more stringent and effective CPFM with lower quality forests. Indeed, throughout the low-income developing world, forest devolution and improved CPFM are now considered major tools for stemming forest degradation.

I find that using the overall CPFM index as a measure, more stringent management is positively, often elastically, and typically significantly correlated with more child labor. Particularly for households exposed to high levels of the institutional characteristics index – clarity, fairness, public participation/democracy – child labor appears to be much higher. On the other hand, households with higher levels of the management tools index are less likely to use child labor and, if they use any child labor, they use less of it.

I find evidence of a wealth paradox with regard to private land and sheep holdings. Though the response is inelastic, households with more agricultural land tend to use more child labor. We concur with other authors who have noted the importance of labor for exploiting land. I just note that common land should be included as well.

I find evidence of a child labor wealth paradox for sheep, but not for cattle, which appears to affect children by reducing child labor, much like education. Mean sheep holdings (9.10) are over six times that of cattle (1.42), which likely are mainly oxen for plowing. Sheep are also by their nature much more reliant on grazing than cattle, which is an activity that is especially supported by children. It is also notable that grazing occurs on common – possibly open access – lands. The zero cost of accessing grazing lands therefore likely distorts child labor, causing more child labor and providing an explanation why sheep would be positively related to child labor.

There are at least two possible explanations for the finding that overall CPFM and institutional characteristics are positively correlated with child labor. First, it is possible that better overall CPFM is really open access in disguise. The institutional characteristics sub-index, which focuses on issues of access clarity, fairness, participation and democracy, is (like the overall CPFM index) positively correlated with total and environmental child labor. It is therefore possible that respondents who perceive their systems as more clear, fair, participatory and democratic perceive them as such because there are few restrictions. In reality, effective CPFM management may therefore be wholly in terms of management tools, which – when the effect is statistically significant – are negatively related to child labor.

Second, while the literature to-date has only analyzed private lands, the results may suggest a child labor wealth paradox for common lands. What would generate such a common land wealth paradox? The literature clearly points to market failures such as missing markets and excessive transactions costs as likely explanations. In the Bolivian Andes, as in most of the low-income developing world, major market and policy failures are quite standard. It is therefore possible that the behavioral "paradox" we observe, like previous paradoxes related to sharecropping (Cheung 1968), excessive risk aversion (Yesuf and Bluffstone 2009) and many other issues discussed in the literature, are household responses to highly imperfect and challenging environments. More effective CPFM may address one market failure, but in interaction with other problems tends to exacerbate child labor.

References

Adhikari, B. (2002) "Property Rights and Natural Resource: Socio-Economic Heterogeneity and Distributional Implications of Common Property Resource Management in Nepal." Paper presented at the Second World Congress of Environmental and Resource Economists, June 24-27, 2002, Monterey, California.

Agrawal, A. (2001) "Commons Property Institutions and Sustainable Governance of Resources." *World Development* 29(10): 1649-1672.

_______ (2000) "Sustainability on the Commons." Paper presented at the 8th Biennial Conference of the International Association for the Study of Common Property in Bloomington, Indiana.

Baland, J.-M., and J.-P. Platteau. (1996) *Halting Degradation of Natural Resources: Is There a Role for Rural Communities?* Oxford: Clarendon Press.

__________________. (1999) "The Ambiguous Impact of Inequality on Local Resource Management." *World Development* 27: 773-788.

Banerjee, A., and E. Duflo. (2007) "The Economic Lives of the Poor." *The Journal of Economic Perspectives* 21(1): 141-168.

Basu, K. (1999) "Child Labor: Cause, Consequence, and Cure, with Remarks on International Labor Standards." *Journal of Economic Literature* 37: 1083-1119.

Basu, K., and P.H. Van (1998) "The Economics of Child Labor." *American Economic Review* 88(3): 412-427.

Basu, K, D. Sanghamitra, and D. Bhaskar. (2010) "Child Labor and Household Wealth: Theory and Empirical Evidence of an Inverted-U." *Journal of Development Economics* 91: 8-14.

Bhalotra, S. (2007) "Is Child Work Necessary?" *Oxford Bulletin of Economics and Statistics* 69(1): 29-55.

Bhalotra. S., and C. Heady. (2003) "Child Labor: The Wealth Paradox." *World Bank Economic Review* 17(2): 197-227.

Bluffstone, R., M. Boscolo, and R. Molina. (2008) "Does Better Common Property Forest Management Promote On-Farm Tree Planting: Evidence from Bolivia." *Environment and Development Economics* 13: 137-170.

Bromley, D.W. (1990) *Essays on the Commons*. Madison: University of Wisconsin Press.

Cameron, A., and P. K. Trivedi. (2005) *Microeconometrics: Methods and Applications*. Cambridge: Cambridge University Press.

Castro, J.C.M., and S. Rist. (1999) *Tipos de Relaciones Bosque-comunidad y Normas Tradicionales de uso y Acceso a la Vegetacion Boscosa*. La Paz: AGRUCO and PROBONA.

Cheung, S. (1968) "Private Property Rights and Sharecropping." *Journal of Political Economy* 76(6): 1107-1122.

Cockburn, J., and B. Dostie. (2007) "Child Work and Schooling: The Role of Household Asset Profiles and Poverty in Rural Ethiopia." *Journal of African Economies* 16: 519-563.

Cooke, P. A. (1998) "Intrahousehold Labor Allocation Responses to Environmental Good Scarcity: A Case Study from the Hills of Nepal." *Economic Development and Cultural Change* 46(4): 807-830.

Cooke, P. A. (2000) "Changes in Intrahousehold Labor Allocation to Environmental Goods Collection: A Case Study from Rural Nepal, 1982 and 1997." IFPRI Discussion Paper no. 87, Washington, D.C., May.

Cooke, P., G. Kohlin, and W.F. Hyde. (2008) "Fuelwood, Forests and Community Management: Evidence from Household Studies." *Environment and Development Economics* 13: 103-135.

Cragg, J. (1971) "Some Statistical Models for Limited Dependent Variables with Applications to the Demand for Durable Goods." *Econometrica* 39: 829-844.

Dasgupta, P. (2000) "Population and Resources: An Explanation of Reproductive and Environmental Externalities." *Population and Development Review* 24(4): 643-689.

Dayton-Johnson, J. (2000) "Choosing Rules to Govern the Commons: A Model with Evidence from Mexico." *Journal of Economic Behavior & Organization* 42(1): 19-41.

Dumas, C. (2007) "Why Do Parents Make their Children Work? A Test of the Poverty Hypothesis in Rural Areas of Burkina Faso." *Oxford Economic Papers* 59(2): 301-329.

Edmonds, E. (2005) "Does Child Labor Decline with Improving Economic Status?" *Journal of Human Resources* 40(1): 77-99.

Edmonds, E., and C. Turk. (2002) "Child Labor in Transition in Vietnam." Policy Research Working Paper no. 2774. The World Bank Development Research Group, Washington, D.C., February.

Filmer, D., and L. Pritchett. (2002) "Environmental Degradation and the Demand for Children: Searching for the Vicious Circle in Pakistan." *Environment and Development Economics* 7: 123-146.

Grootaert, C., and R. Kanbur. (1995) "Child Labour: An Economic Perspective." *International Labour Review* 134: 187-203.

Guann, W. (2003) "From the Help Desk: Bootstrapped Standard Errors." *The Stata Journal* 3(1): 71-80.

Hagemann, F., Y. Diallo, and F. Mehran. (2006) "Global Child Labour Trends 2000 to 2004." International Programme on the Elimination of Child Labour, International Labour Office, Geneva, April.

Heckman, J. (2010) "Building Bridges between Structural and Program Evaluation Approaches to Evaluating Policy." *Journal of Economic Literature* 48(2): 356-398.

__________. (1979) "Sample Selection Bias as a Specification Error." *Econometrica* 47: 153-161.

Heltberg, R. (2001) "Determinants and Impacts of Local Institutions for Common Resource Management." *Environment and Development Economics* 6(2): 183-208.

Kassie, M., J. Pender, M. Yesuf, G. Kohlin, R. Bluffstone, and E. Mulugeta. (2008) "Estimating Returns to Soil Conservation Adoption in the Northern Ethiopian Highlands." *Agricultural Economics Journal* 38: 213-232.

Kohlin, G., and G. Amacher. (2005) "Welfare Implications of Community Forest Plantations in Developing Countries: The Orissa Social Forestry Project." *American Journal of Agricultural Economics* 87(4): 855-869.

Linde-Rahr, M. (2003) "Property Rights and Deforestation: The Choice of Fuelwood Source in Rural Viet Nam." *Land Economics* 79.

Mekonnen, A., and R. Bluffstone. (2007) "Increasing Forest Cover in Ethiopia: Lessons from Economics and International Experience." In Policies to Increase Forest Cover in Ethiopia, proceedings of a policy workshop organized by the Ethiopian Development Research Institute September 18-19, 2007, Addis Ababa.

Moscoso, R.E., and A.D.I. Villanueva. (1997) *Tipos de Relaciones Bosque-comunidad y Normas Tradicionales de acceso al Bosque*. La Paz: PROBONA and PRADEM/CICDA.

Nepal, M., A. Bohara, and R. Berrens. (2007 “Investigating the Impact of Social Networks on Household Forest Conservation Effort in Rural Nepal.” *Land Economics* 83: 174-191.

Olson, M. (1965) *The Logic of Collective Action*. Cambridge: Harvard University Press.

Ostrom, E. (1990) *Governing the Commons: The Evolution of Institutions for Collective Action*. New York: Cambridge University Press.

Perkins, D., S. Radelet, D. Snodgrass, M. Gillis, and M. Roemer. (2001) *Economics of Development*, fifth edition. New York: W.W. Norton.

Pradhan, A.J., and P.J. Parks. (1995) “Environmental and Socioeconomic Linkages of Deforestation and Forest Land Use Change in the Nepal Himalaya." In Hanna, S. and M. Munasinghe (eds.) *Property Rights in a Social and Ecological Context: Case Studies and Design Applications.* Beijer Institute and the World Bank.

Sethi, R., and E. Somanathan. (1996) "The Evolution of Social Norms in Common Property Resource Use." *The American Economic Review* 86(4): 766-788.

Singh, I., L. Squire, and J. Strauss (1986) *Agricultural Household Models: Extensions, Applications, and Policy*. London: Johns Hopkins University Press.

Yesuf, M., and R. Bluffstone. (2009) “Poverty, Risk Aversion and Path Dependence in Low Income Countries: Experimental Evidence from Ethiopia.” *American Journal of Agricultural Economics* 91(4): 1022-1037.

Tables

Table 1. Household Labor Allocations

	Mean Hours	Standard Deviation	Maximum	N
Home production (e.g. cooking, cleaning)	32.98	22.13	123	304
Agriculture	50.37	30.55	147	329
Fuelwood collection	9.77	17.43	175	329
Grazing	28.07	31.09	252	329
Fodder collection	10.37	22.23	252	326
Wage labor	5.31	14.46	110	329
Total	136.87			

Table 2. Percentage of Labor Input by Age and Activity

	Percentage of Total Household Labor Input by Age and Activity					
Age	Home Production	Agricultural Labor	Fuelwood Collection	Grazing	Fodder Collection	Wage Labor
6 –15 years	13.04%	4.97%	7.14%	15.69%	3.92%	0.00%
16 – 35 years	31.68%	35.79%	33.67%	36.86%	32.35%	47.17%
36 – 65 years	42.86%	47.12%	43.88%	39.05%	44.12%	41.51%
> 65 years	12.42%	12.13%	15.31%	8.39%	19.61%	11.32%

Table 3. Definitions and Descriptive Statistics of CPFM Indices.

All indices$_i$ ∈ [0,1] as per (10). Unless noted, survey answers coded such that (5 = definitely, 1 = definitely not)

Overall Common Property Index $\overline{X}$ = 0.31, median = 0.31, σ = 0.15	
Institutional Characteristics Index $\overline{X}$ = 0.45, median = 0.48, σ =.25	**Management Tools Index $\overline{X}$ = 0.17, median = 0.13, σ = 0.15**
SUB-INDICES	
CLARITY OF FOREST ACCESS INDEX $\overline{X}$ = 0.2321, median= 0, σ=0.36 Is the system that determines who is allowed to gather forest products clear and understandable?	**FIXED ALLOTMENTS INDEX** $\overline{X}$ = 0.13, median = 0, σ= 0.53 * Are you allocated a fixed allotment of fuelwood per year? $\overline{X}$ = 0.09, median = 0, σ = 0.28 * Are you allocated a fixed allotment of fodder and grazing rights per year? $\overline{X}$ = 0.18, median = 0, σ = 0.39
FAIRNESS IINDEX $\overline{X}$ = 0.78, median = 0.88, σ = 0.3 * Do you feel you and others can take the amount of forest products that is needed, but not more? $\overline{X}$ = 4.13, median = 5, σ = 1.38 * Are you getting enough forest products to meet your needs, but not more? $\overline{X}$ = 4.10,median = 5, σ = 1.30	**MONITORING INDEX** $\overline{X}$ = 0.27, median= 0.17, σ = 0.32 * Do village authorities carefully monitor who takes what products? $\overline{X}$ = 1.94, median = 1, σ = 1.45 * Do villagers generally watch who takes forest products? $\overline{X}$ = 1.97, median = 1, σ = 1.45 * Are you either formally or informally involved in monitoring common forest lands? $\overline{X}$ = 2.31, median = 1, σ = 1.62
PARTICIPATION & DEMOCRACY INDEX $\overline{X}$ = 0.09, median = 0, σ = 0.17 * Do you have influence on policies for deciding how much forest products people can take? $\overline{X}$ =1.38, median = 1, σ=.9 *Do you help decide who are the managers of the forest? $\overline{X}$ = 1.18, median = 1, σ = 0.68 * Do you expect that in the future you will have the opportunity to manage the common forest? $\overline{X}$ = 1.45, median = 1, σ = 0.99 * Are the managers democratically chosen? $\overline{X}$ = 1.40, median = 1, σ = 1.0	**FORMAL PENALTIES INDEX** $\overline{X}$ = 0.17, median = 0.08, σ = 0.22 * If you took more fuelwood from the forest than you were allowed to take, would you be penalized? $\overline{X}$ = 1.51, median = 0, σ = 0.26 * If you took more fodder from the forest than you were allowed to take, would you be penalized? $\overline{X}$ = 1.51, median = 1, σ = 1.06 * Could you lose some or all of your rights to collect forest products if you were caught taking more than your allotment? $\overline{X}$ = 2.03, median = 1, σ = 1.48
	SOCIAL SANCTION INDEX $\overline{X}$ = 0.38, median = 0.38, σ= 0.38 * Would other villagers be very unhappy with you if they found that you had taken more than your allotment? $\overline{X}$ = 2.7, median = 2, σ = 1.70 * Would you be embarrassed or feel bad if you took more than your allotment of forest products? $\overline{X}$ = 2.47, median =2, σ = 1.61
	LABOR INPUT INDEX $\overline{X}$ = 0.11, median = 0, σ = 0.18 All below (0, 1, 2, 3,>3 days during past month) * Planting common forests $\overline{X}$ = 0.37, median = 0, σ = 0.93 * Watering common forests $\overline{X}$ = 0.51, median = 0, σ = 1.07 * Thinning common forests $\overline{X}$ = 0.55, median = 0, σ = 1.09 * Fertilizing common forests $\overline{X}$ = 0.28, median = 0, σ = 0.77
	PAYMENTS INDEX $\overline{X}$ = 0.03, median = 0, σ = 0.13

	* Do you have to pay to collect fuelwood? $\overline{X}$ = 0.03, median = 0, σ = 0.18 * Do you have to pay to collect fodder and graze? $\overline{X}$ = 0.03, median = 0, σ = 0.17

Table 4. Dependent Variable and First-Stage Potentially Endogenous Variable Descriptive Statistics

	Total Child Labor		**Environmental Child Labor**	
Dependent Variable Definition	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Dummy Variable	0.35	0.48	0.22	0.42
Child Labor in Previous Week	11.97	26.23	5.37	15.74
Potentially Endogenous Independent Variables	**Mean**		**Standard Deviation**	
Overall CPFM Index	0.31		0.15	
Institutional Characteristics Index	0.45		0.25	
Management Tools Index	0.17		0.15	
Children in Household	1.46		1.70	
Fuelwood Used Previous Week (Kg)	12.33		14.92	

Table 5. Descriptive Statistics, Expected Signs and Reasons for Including Variables

Exogenous Covariates	**Mean**	**Expected Sign/Reason for Including**
Dummy variable if household has an improved *lorena* stove (LORENA)	0.47	(-) *Lorena* stove adoption proxies for exogenous labor saving technology adoption and innovation by the household, which reduces child labor.
Log of total estimated on-farm tree years (TREEYEAR)	29.25	(-) Past on-farm tree investments may loosen labor constraints, reducing current demand for child labor
Electricity dummy (ELECTRICITY)	0.026	(-) Households with electricity use less biomass fuels and may have looser labor constraints, reducing current child labor.
Males in household (MALES)	2.00	(?) Adjusts for household composition
Number of females (FEMALES)	1.79	
Tractor plowing dummy (TRACTOR)	0.063	(-) Households who adopt more advanced technologies are likely to utilize less child labor. Tractors also save labor.
Highest level of education of any household member (1=none, 3=some secondary; 9=masters/ Ph.D.) (EDUCATION)	3.70	(-) Households with more educated members are likely to be more willing to invest in all assets, including children.
Years family and ancestors lived in village (1= <5; 7= >100 (YEARS)	6.09	(?) Adjusts for unobservable fixed investments and local social capital.
Spanish language speaker (SPANISH)	0.85	(?) There may be systematic cultural elements associated with use of child labor.
Aymara language speaker (AYMARA)	0.25	
Quechua language speaker (QUECHUA)	0.74	
Number of times meat eaten during previous month (MEAT)	2.25	(-) Proxy for income when production largely non-marketed. *Ceteris paribus*, higher income can be partly spent on children.
Times to store in past week (0 = none; 4 = 6 to 7; 7 = >12) (STORE)	1.58	(?) Households that are more proximate to and/or integrated with markets are likely to have higher incomes, better access to schools and more information, which may reduce child labor. Substitution effects also exist, potentially increasing child labor
Expenditures in Bolivianos/month ($1=8B) (EXPENDITURES)	13.36	
Time to market where respondent most often goes in minutes (TIME)	120.6	
Credit access dummy (BORROW)	0.17	(-) Credit smoothes consumption and reduces risk, facilitating all investments, including in children
Land controlled by household in hectares (LAND)	1.47	(?) Households with more land and animals are wealthier, yielding income effects, but these assets also require labor to exploit, potentially increasing child labor
Number of cattle (CATTLE)	1.42	
Number of sheep (SHEEP)	9.10	
Excluded Exogenous Variables for Estimating First-Stage Regressions		
Village-Level Variables from Survey of Village Leaders		
Department Dummies (La Paz default)		Unobserved heterogeneity
Major ethnic group in village (1 = Quechua; 2 = Aymara; 3= Other) (ETHNIC)	1.30	Possible village-level cultural norms impact all first-stage variables, but likely not child labor directly
Number of households in village (VIL_HH)	535.2	Large and disbursed communities with more area have more difficulty coordinating. CPFM indices likely lower, but effect on children and fuelwood use unclear. Little reason to suspect direct impact on child labor.
Households are clustered rather than disbursed (clustered = 1; 0 = disbursed) (CLUSTER)	0.46	
Estimated total village area (hectares) (AREA)	244,461	
Estimated agricultural area of village (hectares) (AG_AREA)	1598	
Estimated village pasture land (hectares) (PASTURE)	1914	
Timber cutting is explicitly regulated (1=regulated; 0=not regulated) (TIMBER)	0.55	

Fuelwood collection explicitly regulated (1=regulated; 0=not regulated) (FUELWOOD)		Reported village-level management systems, which are related to on-the-ground CPFM, and reflect other norms, but likely do not impact child labor directly
Any regulations on forests are recognized in formal laws (1=formal laws; 0=not by laws) (LAWS)	0.33	
Any regulations on forests are recognized by custom (1=custom; 0=not by custom) (CUSTOM)	0.78	
Villagers can sell their land (1=can sell; 0=cannot sell) (SELL)	0.55	
Household-Level Variables from Household Survey		
Goats (GOATS)	3.34	Animals that represent important wealth, but do not require significant labor, therefore unlikely to affect child labor.
Donkeys (DONKEYS)	0.76	
Men in household 16-35 years old (MALES 16-35)	0.56	Adult composition of the household likely will affect views on actual CPFM system, fertility and fuel use, but not child labor.
Men in household ≥ 65 years old (MALES≥65)	0.18	
Women in household 16-35 years old (FEMALES 16-35)	0.44	
Women in household ≥65 years old (FEMALES≥65)	0.13	
Frequency of using fuelwood (3=2x daily, 0=never) for fuel (FREQ_FW)	1.71	Fuel preferences without regard to amount will likely affect respondent views on CPFM system and fuel use, but not child labor.
Frequency of using dry mosses (3=2x daily, 0=never) for fuel (FREQ_MOSS)	0.77	
Frequency of using gas (3=2x daily, 0=never) for fuel (FREQ_GAS)	1.42	
Frequency of using crop residues (3=2x daily, 0=never) for fuel (FREQ_CROPRES)	0.25	
Rank of animal bedding (1 lowest, 7 highest) from own trees (BED)	0.71	Preferences related to on-farm trees relate to fuelwood consumption and CPFM system, but not child labor
Rank of shade/ambience (1 lowest, 7 highest) from own trees (SHADE)	3.56	

Table 6. First Stage Regression Results Full Sample

OLS with Robust Standard Errors Adjusted for Village Clustering (p values in parentheses)

	CPFM Indices				
Dependent Variables ⇒	**Overall Common Property**	**Institutional Characteristics**	**Management Tools**	**Children**	**Fuelwood Use (Kilograms)**
Exogenous Covariates					
LORENA	0.0272 (0.22)	0.086 (0.01)***	0.0249 (0.21)	0.0741 (0.49)	-1.5632 (0.46)
TREEYEARS	0.0001 (0.80)	0.0002 (0.34)	-0.0001 (0.60)	-0.0009(0.23)	-0.0073 (0.68)
ELECTRICITY	-0.0110 (0.77)	-0.0326 (0.60)	0.0105 (0.79)	-0.947 (0.00)***	-2.1475 (0.57)
MALES	0.0076 (0.28)	0.0118 (0.21)	0.0034 (0.69)	0.861 (0.00)***	1.1309 (0.17)
FEMALES	0.0036 (0.64)	0.0108 (0.32)	-0.0037 (0.68)	0.866 (0.00)***	0.8906 (0.34)
TRACTOR	-0.0343 (0.27)	-0.0470 (0.46)	-0.0217 (0.62)	0.2002 (0.36)	-0.1277 (0.97)
EDUCATION	-0.0126 (0.01)***	-0.024 (0.00)***	-0.0017 (0.77)	-0.046 (0.10)*	-0.2294 (0.66)
YEARS	0.0039 (0.64)	0.0049 (0.69)	0.0030 (0.75)	-0.081 (0.08)*	0.3977 (0.65)
SPANISH	0.0058 (0.77)	0.0221 (0.50)	-0.0105 (0.61)	-0.098 (0.48)	1.7438 (0.39)
AYMARA	0.0143 (0.74)	-0.0083 (0.88)	0.0369 (0.40)	-0.145 (0.49)	-0.0078 (0.99)
QUECHUA	-0.0784 (0.06)*	-0.0308 (0.59)	-0.13 (0.00)***	-0.072 (0.79)	5.4426 (0.09)*
MEAT	0.0147 (0.09)*	0.0254 (0.06)*	0.0040 (0.68)	0.0581 (0.28)	-0.1320 (0.87)
STORE	0.0072 (0.18)	0.0117 (0.11)	0.0026 (0.68)	0.0147 (0.68)	-0.1226 (0.85)
EXPENDITURE	-0.0004 (0.22)	-0.0003 (0.62)	-0.001 (0.10)*	0.0009 (0.68)	-0.0056 (0.88)
TIME	0.0001 (0.15)	0.0001 (0.03)**	0.0000 (0.79)	0.0000 (0.93)	-0.0046 (0.27)
BORROW	0.0464 (0.05)**	0.0115 (0.75)	0.081 (0.0)***	0.1316 (0.44)	-3.7944 (0.11)
LAND	0.0000 (0.32)	0.0000 (0.33)	0.0000 (0.35)	0.0000 (0.89)	0.0000 (0.29)
CATTLE	-0.0078 (0.11)	-0.017 (0.01)***	0.0013 (0.77)	0.0130 (0.54)	0.2213 (0.63)
SHEEP	0.0002 (0.38)	-0.0001 (0.84)	0.0004 (0.07)*	-0.003 (0.04)**	0.0446 (0.42)
CONSTANT	0.2817 (0.07)*	0.4000 (0.085)*	0.1634 (0.33)	-0.995 (0.28)	1.6693 (0.94)
Excluded Instruments					
COCHABAMBA	0.1294 (0.20)	0.1852 (0.21)	0.0736 (0.48)	0.1649 (0.79)	-9.6057 (0.38)
ORURO	-0.0769 (0.44)	-0.2240 (0.14)	0.0702 (0.51)	0.4034 (0.52)	-9.7384 (0.41)
CHUQUISACA	0.1979 (0.06)*	0.2646 (0.08)*	0.1312 (0.22)	0.1911 (0.78)	-5.7399 (0.61)
POTOSI	-0.0489 (0.62)	-0.1873 (0.19)	0.0894 (0.38)	0.0177 (0.98)	-14.2741 (0.21)
ETHNIC	0.0373 (0.46)	0.0539 (0.45)	0.0207 (0.69)	0.0314 (0.92)	-1.2569 (0.85)
VIL_HH	0.0000 (0.33)	0.0000 (0.20)	0.0000 (0.97)	0.0000 (0.84)	-0.0009 (0.37)
CLUSTER	-0.0473 (0.03)**	-0.0649 (0.07)*	-0.0296 (0.21)	0.1934 (0.13)	-1.8444 (0.29)
AREA	0.0000 (0.65)	0.0000 (0.79)	0.0000 (0.46)	0.0000 (0.06)*	0.0000 (0.36)
AG_AREA	0.0000 (0.34)	0.0000 (0.92)	0.0000 (0.06)*	0.0000 (0.66)	-0.0001 (0.75)
PASTURE	0.0645 (0.02)**	0.0790 (0.03)**	0.0501 (0.11)	0.0746 (0.66)	-3.8272 (0.19)
TIMBER	-0.1048 (0.00)***	-0.1028 (0.04)**	-0.11 (.01)***	-0.260 (0.23)	1.5214 (0.61)
FUELWOOD	0.0637 (0.15)	0.0222 (0.73)	0.105 (0.03)**	0.1501 (0.56)	4.7506 (0.26)
LAWS	0.0373 (0.16)	0.0685 (0.08)*	0.0062 (0.83)	-0.161 (0.36)	2.3784 (0.39)
CUSTOM	-0.0431 (0.39)	-0.1047 (0.16)	0.0184 (0.75)	0.5154 (0.06)*	-0.5991 (0.87)
SELL	-0.0016 (0.95)	-0.0208 (0.62)	0.0176 (0.59)	-0.368 (0.04)**	4.0626 (0.12)
GOATS	-0.0016 (0.17)	-0.0004 (0.79)	-0.003 (0.02)**	0.0051 (0.43)	0.0336 (0.83)
DONKEYS	-0.0013 (0.88)	0.0012 (0.91)	-0.0037 (0.67)	-0.045 (0.16)	0.8011 (0.26)
MALES 16-35	-0.0075 (0.56)	-0.0121 (0.52)	-0.0029 (0.86)	-0.678 (0.00)***	0.5050 (0.81)
MALES ≥ 65	-0.0023 (0.91)	-0.0090 (0.78)	0.0043 (0.86)	-0.138 (0.30)	-1.0854 (0.60)
FEMALES 16-35	0.0127 (0.44)	-0.0043 (0.85)	0.0297 (0.08)*	-0.317 (0.00)***	-2.0040 (0.30)
FEMALES ≥ 65	-0.0090 (0.69)	0.0188 (0.63)	-0.0369 (0.13)	-0.454 (0.00)***	0.7594 (0.76)
FREQ_FW	0.0059 (0.48)	-0.0021 (0.88)	0.0138 (0.13)	0.0038 (0.94)	5.552 (0.00)***
FREQ_MOSS	0.0055 (0.83)	0.0123 (0.69)	-0.0012 (0.97)	0.0152(0.90)	4.7528 (0.14)
FREQ_GAS	0.0031 (0.73)	0.0127 (0.39)	-0.0066 (0.53)	0.0999 (0.05)**	-0.7553 (0.43)
FREQ_CROPRES	0.0345 (0.01)***	0.0240 (0.29)	0.05 (0.00)***	0.1473 (0.09)*	2.0802 (0.21)
BED	-0.0071 (0.11)	-0.0009 (0.89)	-0.01 (0.0)***	0.0234 (0.38)	-0.3953 (0.40)
SHADE	-0.0028 (0.34)	-0.0040 (0.36)	-0.0015 (0.58)	-0.012 (0.47)	0.3050 (0.39)

F(46, 207)	11.73	8.97	8.97	58.48	24.40
Prob > F	0.00***	0.000***	0.00***	0.000***	0.000***
Adj R-squared	0.4129	0.34	0.34	0.85	0.33
N	254	254	254	254	254

P values in parentheses *, **, *** Indicate Significance at Least at the 10%, 5% and 1% Levels.

Table 7. 2SLS IV Regression Models of Child Labor with Different CPFM Measures

Robust Standard Errors Adjusted for Village Clustering

	2SLS IV Regression Total Child Labor				**2SLS IV Regression Environmental Child Labor[1]**			
CPFM Definition ⇒	**Overall Common Property (most aggregated)**		**Institutional Characteristics and Management Tools**		**Overall Common Property (most aggregated)**		**Institutional Characteristics and Management Tools**	
Sample Used ⇒	Full Sample	HHs[2] with Children[3]	Full Sample	HHs with Children n	Full Sample	HHs with Children	Full Sample	HHs with Children
	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect
Endogenous Variables (instrumented based on testing)								
COMMON PROPERTY INDEX	20.6861 (0.28)	19.9891 (0.42)			19.6222 (0.06)*	18.6708 (0.12)		
INSTITUTIONAL CHARACTERISTICS			31.9368 (0.00)***	41.5884 (0.01)***			23.4050 (0.00)***	29.0447 (0.00)***
MANAGEMENT TOOLS			-45.7318 (0.02)**	-59.8952 (0.01)***			-25.4897 (0.02)**	-34.2644 (0.04)**
CHILDREN	9.1260 (0.00)***		9.0458 (0.00)***		3.2053 (0.03)**		3.1548 (0.03)**	
FUELWOOD USE	0.4768 (0.01)***	0.5295 (0.02)**	0.5327 (0.01)***	0.5398 (0.03)**	0.2035 (0.05)**	0.2389 (0.06)*	0.2387 (0.04)**	0.2454 (0.11)
Exogenous Covariates								
LORENA	-0.6839 (0.83)	0.0426 (0.04)**	-6.2624 (0.18)	-9.5523 (0.13)	0.4461 (0.82)	2.7491 (0.35)	-3.0657 (0.32)	-4.5744 (0.27)
TREEYEAR	0.0408 (0.00)***	-8.5022 (0.24)	0.0261 (0.03)**	0.0267 (0.34)	0.0093 (0.25)	0.0007 (0.96)	0.0001 (0.99)	-0.0093 (0.59)
ELECTRICITY	0.8335 (0.80)	2.1404 (0.29)	1.1715 (0.80)	-9.9268 (0.14)	-5.3649 (0.00)***	-11.6679 (0.00)***	-5.1521 (0.02)**	-12.5567 (0.00)***
MALES	-3.2466 (0.13)	5.0623 (0.01)***	-3.2123 (0.20)	1.8607 (0.43)	-1.1962 (0.35)	0.6613 (0.53)	-1.1747 (0.41)	0.4868 (0.70)
FEMALES	-1.2160 (0.62)	-10.7265 (0.17)	-1.4986 (0.56)	3.9371 (0.01)***	0.1285 (0.91)	2.2349 (0.05)**	-0.0494 (0.97)	1.5329 (0.10)*
TRACTOR	-6.9515 (0.20)	-2.6440 (0.16)	-4.8994 (0.40)	-12.9631 (0.06)*	-3.9439 (0.22)	-8.9926 (0.03)**	-2.6520 (0.47)	-10.3879 (0.01)***
EDUCATION	0.0625 (0.93)	1.8248 (0.21)	0.2185 (0.76)	-2.8487 (0.13)	-0.0737 (0.84)	-1.4486 (0.11)	0.0245 (0.95)	-1.5763 (0.09)*
YEARS	2.1042 (0.13)	1.9450 (0.85)	2.0337 (0.12)	1.8170 (0.24)	1.1635 (0.08)*	1.2401 (0.16)	1.1190 (0.05)**	1.2352 (0.14)
SPANISH	2.6062 (0.53)	-5.1690 (0.47)	3.1118 (0.44)	3.0327 (0.75)	1.0698 (0.60)	1.4820 (0.74)	1.3881 (0.46)	2.1605 (0.60)
AYMARA	-3.2400 (0.50)	3.8040 (0.66)	1.3056 (0.81)	3.4186 (0.63)	-0.8892 (0.63)	-0.3160 (0.90)	1.9723 (0.42)	5.0412 (0.18)
QUECHUA	3.7891 (0.52)	3.2249 (0.10)*	1.2843 (0.84)	3.1917 (0.71)	4.7944 (0.06)*	7.3069 (0.05)**	3.2175 (0.25)	6.9249 (0.08)*
MEAT	0.6872 (0.60)	-0.7319 (0.60)	0.1171 (0.93)	2.7259 (0.19)	0.6813 (0.46)	2.4542 (0.04)**	0.3223 (0.73)	2.1429 (0.09)*
STORE	-1.3478 (0.09)*	0.2014 (0.03)**	-1.0571 (0.22)	-1.2893 (0.43)	-0.4994 (0.24)	0.2191 (0.79)	-0.3164 (0.50)	-0.1286 (0.90)
EXPENDITURES	0.1417 (0.03)**	-0.0007 (0.96)	0.0856 (0.22)	0.1244 (0.23)	0.0812 (0.04)**	0.1291 (0.04)**	0.0458 (0.33)	0.0811 (0.26)
TIME	-0.0044 (0.71)	-3.1967 (0.67)	-0.0100 (0.41)	-0.0064 (0.60)	-0.0054 (0.19)	-0.0032 (0.37)	-0.0089 (0.06)*	-0.0068 (0.13)
BORROW	-1.1538 (0.85)	0.0000 (0.97)	3.8202 (0.53)	2.3135 (0.75)	-0.2262 (0.95)	-0.8333 (0.86)	2.9051 (0.44)	2.6042 (0.59)
LAND	0.0000	1.2105	0.0000	-0.0001	0.0000	-0.0001	0.0000	-0.0001

	(0.96)	(0.45)	(0.46)	(0.42)	(0.09)*	(0.36)	(0.01)***	(0.07)*
CATTLE	0.7928 (0.32)	0.0426 (0.04)**	1.1685 (0.13)	2.1347 (0.13)	0.4969 (0.30)	0.9215 (0.39)	0.7334 (0.13)	1.4980 (0.12)
SHEEP	0.0407 (0.42)	0.0621 (0.13)	0.0557 (0.29)	0.0808 (0.03)**	0.0270 (0.40)	0.0407 (0.20)	0.0364 (0.28)	0.0524 (0.07)*
CONSTANT	-25.8652 (0.06)*	-28.7407 (0.27)	-22.5031 (0.11)	-21.4004 (0.37)	-19.2899 (0.00)***	-25.6165 (0.05)**	-17.1733 (0.01)***	-21.0374 (0.06)*
Goodness of Fit Tests								
R^2	0.34	0.30	0.33	0.30	0.25	0.29	0.22	0.27
Wald test	1046.53 d.f. = 22 (prob. > $\chi 2$=0.00)	1244.09 d.f. = 21 (prob. > $\chi 2$=0.00)	3641.96 d.f. = 23 (prob. > $\chi 2$=0.00)	833.95 d.f. = 22 (prob. > $\chi 2$=0.00)	1166.3 d.f. = 22 (prob. > $\chi 2$=0.00)	1798.76 d.f. = 22 (prob. > $\chi 2$=0.00)	1750.59 d.f. = 23 (prob. > $\chi 2$=0.00)	1580.89 d.f. = 22 (prob. > $\chi 2$=0.00
Exogeneity Tests								
Wu Hausman F Test	2.38 (p=0.07)	0.762 (p=0.47)	2.91 (p=0.02)	1.31 (p=0.27)	2.21 (p=0.08)	0.62 (p=0.54)	3.52 (p=0.01)	1.93 (p=0.13)
Durban χ^2 Test	7.70 (0.05)	1.79 (p=0.41)	12.44 (p=0.01)	4.61 (p=0.20)	7.17 (0.07)	1.46 (p=0.48)	14.89 (p=0.00)	6.67 (p=0.08)
Overidentifying Restrictions Tests								
Sargan	27.64 (p=0.28)	34.33 (p=0.08)	18.07 (p=0.75)	26.65 (p=0.27)	33.0 (p=0.10)	38.80 (p=0.02)	20.84 (p=0.59)	28.53 (p=0.20)
Basmann	25.27 (p=0.39)	30.87 (p=0.16)	15.90 (p=0.86)	22.47 (p=0.49)	30.91 (0.16)	36.29 (p=0.05)	18.51 (p=0.73)	24.42 (p=0.38)
Weak Instruments – Shea's Partial R^2								
COMMON PROPERTY INDEX	0.30	0.35	-		0.30	0.35		
INSTITUTIONAL CHARACTERISTICS			0.36	0.43			0.36	0.43
MANAGEMENT TOOLS			0.25	0.30			0.25	0.30
CHILDREN	0.41		0.41		0.41		0.41	
FUELWOOD USE	0.31	0.36	0.31	0.36	0.31	0.36	0.31	0.36
Observations	**254**	**150**	**254**	**150**	**254**	**150**	**254**	**150**

P values in parentheses *, **, *** indicate significance at least at the 10%, 5% and 1% levels.

Table 8. Probit Models of Child Labor with Different CPFM Measures

Robust Standard Errors Adjusted for Village Clustering

	Total Child Labor				Environmental Child Labor[1]			
CPFM Definition ⇒	**Overall Common Property (most aggregated)**		**Institutional Characteristics and Management Tools**		**Overall Common Property (most aggregated)**		**Institutional Characteristics and Management Tools**	
Sample Used ⇒	Full Sample	HHs[2] with Children[3]	Full Sample	HHs with Children	Full Sample	HHs with Children	Full Sample	HHs with Children
	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect (p value)	Marginal Effect
Potentially Endogenous Variables (not instrumented based on testing)								
COMMON PROPERTY INDEX	0.3661 (0.12)	0.2290 (0.46)			0.1613 (0.40)	0.2957 (0.38)		
INSTITUTIONAL CHARACTERISTICS			0.6138 (0.00)***	0.5144 (0.01)***			0.2324 (0.10)*	0.3682 (0.11)
MANAGEMENT TOOLS			-0.5834 (0.04)**	-0.5528 (0.05)**			-0.1687 (0.32)	-0.1768 (0.55)
CHILDREN	0.2243 (0.00)***		0.2433 (0.00)***		0.1242 (0.00)***		0.1255 (0.00)***	
FUELWOOD USE	0.0085 (0.00)***	0.0079 (0.00)***	0.0086 (0.00)***	0.0076 (0.00)***	0.0056 (0.00)***	0.0069 (0.00)***	0.0054 (0.00)***	0.0067 (0.00)***
Exogenous Covariates								
LORENA	0.1137 (0.14)	0.1518 (0.03)**	0.0158 (0.82)	0.0389 (0.56)	0.0495 (0.31)	0.0843 (0.34)	0.0105 (0.85)	0.0263 (0.77)
TREEYEAR	0.0012 (0.02)**	0.0025 (0.00)***	0.0011 (0.03)**	0.0023 (0.00)***	0.0000 (0.94)	-0.0004 (0.66)	0.0000 (0.95)	-0.0004 (0.57)
ELECTRICITY	0.2997 (0.07)*	0.1516 (0.40)	0.3711 (0.03)**	0.1785 (0.25)	0.2107 (0.27)	0.0697 (0.80)	0.2246 (0.27)	0.0725 (0.80)
MALES	-0.0268 (0.60)	0.0237 (0.43)	-0.0352 (0.53)	0.0288 (0.39)	-0.0033 (0.92)	0.0574 (0.16)	-0.0039 (0.91)	0.0584 (0.17)
FEMALES	-0.0196 (0.72)	0.0638 (0.10)*	-0.0381 (0.53)	0.0588 (0.12)	-0.0172 (0.59)	0.0541 (0.11)	-0.0209 (0.51)	0.0512 (0.12)
TRACTOR	0.2913 (0.05)**	0.3138 (0.01)***	0.2968 (0.04)**	0.2918 (0.02)**	Dropped, because model would not converge			
EDUCATION	0.0367 (0.07)*	0.0193 (0.53)	0.0422 (0.04)**	0.0207 (0.52)	-0.0175 (0.44)	-0.0394 (0.36)	-0.0143 (0.50)	-0.0347 (0.40)
YEARS	-0.0089 (0.81)	-0.0006 (0.99)	-0.0103 (0.79)	-0.0024 (0.95)	0.0245 (0.28)	0.0399 (0.30)	0.0229 (0.32)	0.0387 (0.32)
SPANISH	-0.0092 (0.94)	-0.1110 (0.50)	0.0062 (0.95)	-0.0982 (0.54)	-0.1378 (0.25)	-0.2954 (0.17)	-0.1289 (0.26)	-0.2876 (0.18)
AYMARA	0.0736 (0.65)	-0.0277 (0.87)	0.1448 (0.38)	0.0415 (0.81)	-0.0935 (0.43)	-0.1690 (0.36)	-0.0783 (0.50)	-0.1400 (0.44)
QUECHUA	0.0665 (0.71)	-0.0515 (0.79)	0.0501 (0.78)	-0.0557 (0.77)	-0.0089 (0.96)	-0.0510 (0.83)	-0.0216 (0.89)	-0.0582 (0.80)
MEAT	-0.0020 (0.96)	-0.0102 (0.82)	-0.0207 (0.64)	-0.0194 (0.69)	-0.0045 (0.89)	0.0087 (0.89)	-0.0122 (0.71)	0.0012 (0.99)
STORE	-0.0129 (0.53)	0.0049 (0.87)	-0.0066 (0.78)	0.0041 (0.90)	-0.0197 (0.24)	-0.0144 (0.62)	-0.0176 (0.29)	-0.0153 (0.60)
EXPENDITURES	0.0009 (0.55)	0.0002 (0.93)	-0.0001 (0.95)	-0.0008 (0.69)	0.0015 (0.17)	0.0027 (0.13)	0.0012 (0.33)	0.0024 (0.23)
TIME	0.0001 (0.69)	0.0001 (0.43)	0.0000 (0.87)	0.0000 (0.78)	0.0000 (0.46)	0.0000 (0.85)	-0.0001 (0.30)	0.0000 (0.88)
BORROW	0.0155	-0.0288	0.0746	0.0218	-0.0814	-0.1558	-0.0662	-0.1294

	(0.89)	(0.79)	(0.56)	(0.84)	(0.21)	(0.16)	(0.34)	(0.28)
LAND	0.0000 (0.35)	0.0000 (0.70)	0.0000 (0.84)	0.0000 (0.47)	0.0000 (0.05)**	0.0000 (0.04)**	0.0000 (0.03)**	0.0000 (0.02)**
CATTLE	-0.0148 (0.32)	0.0252 (0.20)	-0.0089 (0.49)	0.0329 (0.07)*	0.0021 (0.85)	0.0271 (0.18)	0.0038 (0.71)	0.0322 (0.08)*
SHEEP	-0.0009 (0.38)	-0.0012 (0.25)	-0.0006 (0.52)	-0.0010 (0.35)	0.0046 (0.01)***	0.0082 (0.06)*	0.0045 (0.01)***	0.0077 (0.07)*
Pseudo R^2	0.39	0.15	0.42	0.18	0.37	0.23	0.37	0.24
Wald test of exogeneity based on IV Probit	χ2=3.66 (p=0.30) d.f. = 3	χ2=3.80 (p=0.15) d.f. = 2	χ2=3.56 (p=0.47) d.f.=4	X2=3.71 (p=0.29) d.f.=3	χ2=12.75 (p=0.01) d.f. = 3	χ2=10.77 (p=0.00) d.f. = 2	χ2=13.12 (p=0.01) d.f. = 4	χ2=13.29 (p=0.0) d.f. = 3
Wald χ2	298.82 d.f. = 22 (prob. > χ2=0.00)	193.22 d.f. = 21 (prob. > χ2=0.00)	217.70 d.f. = 23 (prob. > χ2=0.00)	201.32 d.f. = 22 (prob. > χ2=0.00)	416.61 d.f. =21 (prob. > χ2=0.00)	146.6 d.f. =20 (prob. > χ2=0.00)	528.41 d.f. =22 (prob. > χ2=0.00)	154.67 d.f. =21 (prob. > χ2=0.00)
Observations	288	170	288	170	267	159	267	159

P values in parentheses *, **, *** indicate significance at least at the 10%, 5% and 1% levels.

[1] In models of environmental child labor, including ownership of a tractor caused the variance matrix to be close to singular. It was therefore necessary to drop that variable. Wald χ^2 tests of endogeneity indicate that the package of potentially endogenous variables are indeed endogenous. Due to limited observations, marginal effects for the IV Probit could not be generated. For comparability, Probit results are therefore reported, but IV Probit coefficient estimates available from the author.
[2] HHs stands for "households."
[3] Of course, because no households are without children, the variable CHILDREN is dropped from these models.

Table 9. Second Step of Double Hurdle Truncated Regression Models of Child Labor with Different CPFM Measures

Bootstrapped (1000 Repetitions) Robust Standard Errors Adjusted for Village Clustering

	Total Child Labor				**Environmental Child Labor**			
CPFM Definition ⇒	**Overall Common Property (most aggregated)**		**Institutional Characteristics and Management Tools**		**Overall Common Property (most aggregated)**		**Institutional Characteristics and Management Tools**	
Sample Used ⇒	Full Sample	HHs with Children[3]	Full Sample	HHs with Children	Full Sample	HHs with Children	Full Sample	HHs with Children
	Marginal Effects (p value)		Marginal Effects (p value)		Marginal Effects (p value)		Marginal Effects (p value)	
Potentially Endogenous Variables – <u>Predicted Values used based on testing</u>								
COMMON PROPERTY INDEX	100.3934 (0.33)	25.7955 (0.84)			129.9483 (0.13)	48.8466 (0.60)		
INSTITUTIONAL CHARACTERISTICS			80.7908 (0.19)	51.0544 (0.50)			71.5737 (0.17)	35.7319 (0.55)
MANAGEMENT TOOLS			-38.8311 (0.67)	-173.3654 (0.08)*			48.3475 (0.63)	-4.2001 (0.97)
CHILDREN	-34.3583 (0.00)***		-31.7597 (0.00)***		-20.9937 (0.01)***		-20.8453 (0.03)**	
FUELWOOD USE	0.6498 (0.45)	0.7995 (0.42)	0.6309 (0.47)	0.8056 (0.42)	0.1224 (0.84)	-0.0073 (0.99)	0.1163 (0.87)	-0.0125 (0.99)
Exogenous Variables								
LORENA	-11.7112 (0.40)	-2.0479 (0.90)	-18.0569 (0.24)	-15.2264 (0.38)	1.3843 (0.97)	8.3770 (0.48)	-0.0422 (0.99)	5.8753 (0.62)
TREEYEAR	-0.0202 (0.77)	0.0195 (0.77)	-0.0202 (0.77)	0.0127 (0.85)	-0.0491 (0.67)	0.0364 (0.77)	-0.0510 (0.64)	0.0316 (0.78)
ELECTRICITY	-24.2171 (0.47)	-27.2640 (0.53)	-25.2336 (0.42)	-27.9337 (0.47)	-47.1594 (0.07)*	-48.6782 (0.09)*	-47.4600 (0.10)*	-49.1591 (0.10)*
MALES	5.3240 (0.16)	5.9340 (0.16)	5.0281 (0.20)	5.1236 (0.24)	1.9838 (0.42)	3.6462 (0.17)	2.0433 (0.44)	3.7043 (0.21)
FEMALES	12.2839 (0.00)***	8.9888 (0.03)**	11.3670 (0.01)***	7.8215 (0.08)*	7.1487 (0.02)***	5.1906 (0.09)*	6.9850 (0.03)***	4.9589 (0.13)
TRACTOR	-177.444 (0.01)***	-210.8117 (0.01)***	-159.870 (0.02)**	-171.9673 (0.02)**	Dropped because model would not converge			
EDUCATION	-12.0095 (0.01)**	-17.4829 (0.00)***	-11.7550 (0.02)***	-15.7895 (0.01)***	-6.6519 (0.06)*	-10.8419 (0.01)***	-6.5476 (0.07)*	-10.5678 (0.02)**
YEARS	12.8433 (0.04)**	11.4637 (0.05)**	10.8223 (0.09)*	8.3147 (0.16)	10.7074 (0.09)*	7.5311 (0.21)	10.0988 (0.16)	6.5266 (0.36)
SPANISH	1.8814 (0.91)	-10.1478 (0.57)	4.3952 (0.80)	-3.4975 (0.84)	5.6768 (0.56)	-1.1904 (0.91)	6.1439 (0.54)	-0.3459 (0.98)
AYMARA	-17.9526 (0.54)	-54.6092 (0.19)	-13.4320 (0.66)	-42.5838 (0.30)	-21.4775 (0.68)	-57.0174 (0.39)	-19.4653 (0.73)	-53.2115 (0.45)
QUECHUA	8.0943 (0.80)	-35.1681 (0.42)	-6.0979 (0.88)	-58.7176 (0.22)	-0.5123 (0.99)	-36.0398 (0.60)	-2.1758 (0.97)	-38.6503 (0.60)
MEAT	9.2836 (0.18)	12.8783 (0.12)	8.2531 (0.26)	10.1989 (0.24)	8.0392 (0.17)	11.2873 (0.07)*	7.8650 (0.28)	10.9075 (0.14)
STORE	-13.3155 (0.01)***	-14.5686 (0.01)***	-13.2957 (0.01)***	-14.1558 (0.02)**	-8.9363 (0.10)*	-10.1257 (0.10)*	-9.0246 (0.13)	-10.2595 (0.12)
EXPENDITURES	0.1023 (0.67)	0.1531 (0.53)	0.1132 (0.62)	0.1678 (0.47)	0.0027 (0.99)	0.0007 (0.99)	0.0063 (0.97)	0.0056 (0.98)
TIME	0.0075	-0.0015	0.0057	-0.0043	0.0061	0.0017	0.0059	0.0013

	(0.84)	(0.97)	(0.87)	(0.90)	(0.79)	(0.94)	(0.81)	(0.96)
BORROW	-4.2835 (0.85)	-13.5779 (0.64)	-4.3255 (0.84)	-12.5863 (0.61)	9.4535 (0.81)	10.0981 (0.80)	9.3687 (0.83)	9.9975 (0.81)
LAND	0.0000 (0.96)	-0.0001 (0.86)	-0.000 (0.82)	-0.0002 (0.65)	-0.0002 (0.49)	-0.0001 (0.61)	-0.0002 (0.45)	-0.0002 (0.54)
CATTLE	2.5572 (0.51)	-1.6437 (0.68)	2.8551 (0.43)	-0.5701 (0.87)	3.9454 (0.33)	1.3045 (0.68)	3.9947 (0.26)	1.4171 (0.67)
SHEEP	1.4633 (0.00)***	1.8683 (0.00)***	1.4307 (0.00)***	1.7486 (0.00)***	0.9910 (0.01)***	1.1742 (0.01)***	0.9816 (0.02)**	1.1561 (0.02)**
Wald test of exogeneity based on IV Probit	63.03 d.f. = 22 (prob. > $\chi2$=0.00)	56.37 d.f. = 21 (prob. > $\chi2$=0.00)	76.12 d.f. = 23 (prob. > $\chi2$=0.00)		52.37 d.f. = 21 (prob. > $\chi2$=0.00)		103.46 d.f. = 22 (prob. > $\chi2$=0.00)	
Observations	101	101	101		66		66	

P values in parentheses *, **, *** indicate significance at least at the 10%, 5% and 1% levels.

Table 10. Average Treatment Effects on the Treated (ATT) Using Nearest Neighbor Propensity Score Matching

	Total Child Labor				Environmental Child Labor			
	Continuous Variable		Dummy Variable		Continuous Variable		Dummy Variable	
	Full Sample	HHs with Children[3]	Full Sample	HHs with Children	Full Sample	HHs with Children	Full Sample	HHs with Children
	ATT (t statistic)		ATT (t statistic)		ATT (t statistic)		ATT (t statistic)	
COMMON [1, 4] PROPERTY INDEX	13.633*** (3.807)	9.035 (1.293)	0.242*** (0.089)	0.136 (0.981)	6.63*** (3.329)	4.397 (1.144)	0.181** (2.466)	0.073 (0.538)
INSTITUTIONAL[2, 5] CHARACTERISTICS	12.87*** (4.166)	6.859 (0.708)	0.181* (1.798)	-0.099 (-0.484)	5.762*** (3.814)	0.786 (0.146)	0.080 (0.95)	-0.245 (-1.310)
MANAGEMENT[3, 6] TOOLS	-0.265 (0.029)	5.760 (0.913)	-0.228 (-1.513)	-0.138 (0.827)	0.456 (0.068)	4.076 (1.046)	0.041 (0.339)	0.066 (0.421)

t statistics in parentheses *, **, *** indicate significance at least at the 10%, 5% and 1% levels.

[1] For all models using this treatment and full sample N = 329. Total treated 189 and 173 matched. Matched treated = 163. Matched control = 80.
[2] For all models using this treatment and full sample N = 329. Total treated 189 and 174 matched. Matched treated = 189. Matched control = 74.
[3] For all models using this treatment and full sample N = 329. Total treated 188 and 167 matched. Matched treated = 188. Matched control = 82.
[4] For all models using this treatment and sub-sample of households with children N = 190. Total treated 129 and 119 matched. Matched treated = 129. Matched control = 37.
[5] For all models using this treatment and sub-sample of households with children N = 190. Total treated 125 and 118 matched. Matched treated = 125. Matched control = 38.
[6] For all models using this treatment and sub-sample of households with children N = 190. Total treated 107 and 94 matched. Matched treated = 107. Matched control = 42.