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Child Labor and Household Land Holding: Theory and Empirical Evidence from Zimbabwe

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SUMMARY

The relationship between rural household productive assets and child labor in developing countries is complex. Some empirical evidence shows that child labor tends to increase as land holding increases, or there is an inverted U-shaped curve relationship between the probability of putting children to work and land holding. This paper shows that the relationship between use of children as laborers and land holding is nuanced. Child labor generally decreases as per capita land holding increases, but there can be an upward bump in the relationship between child labor and landholding near the middle of the range of land per capita. The bump can be explained theoretically by the relationship between the marginal productivity of a child worker on the farm and the marginal value placed on his/her education at different levels of wealth. This pattern is repeated in three surveys conducted in Zimbabwe, in 2001, 2007–8, and 2010–11. From the perspective of policy making, the policy maker should be alerted that the programs to promote school retention should not necessarily focus only on the poorest households in rural areas. There is a high probability that middle-wealth households put their children to work, and this probability may change by some other factors such as gender of child and agro-ecological conditions.

1. Introduction

Child labor is common around the world, particularly in developing countries. In 2012, sub-Saharan Africa (SSA) had the highest rates of working children, with 26.2% of children aged 5–14 being employed (Diallo, Etienne, & Mehran, 2013). SSA is one of the poorest regions of the world, and it also has one of the youngest populations (Bongaarts & Casterline, 2013). These facts raise concerns about the employment of children; long-run poverty reduction and growth may be compromised by use of children in productive activities rather than investing in human capital through schooling (Heady, 2003). Most working children in rural areas of SSA are involved in agriculture and are frequently employed by their parents (International Labour Organization, 1996; Edmonds & Pavcnik, 2005a, 2005b). As reductions in child labor can improve economic growth in the long-run, factors associated with use of child labor in agriculture should be identified.

Zimbabwe is a SSA country where achievements in schooling are particularly noteworthy (Larochelle, Alwang, & Taruvinga, 2014). Achievements in education and provision of other social services since Independence, however, are threatened by ongoing economic crises. The people of Zimbabwe have faced severe economic difficulties in the recent past. In the decade beginning in 2000 inflation rates began to grow and, by 2008, one of the more severe hyper-inflations in recent memory racked the economy (see Appendix A for a description of the hyperinflation). During 2000–08, recurring droughts, a mismanaged land reform, and structural problems associated with agriculture led to widespread suffering and emigration of professional workers including teachers and nurses. In a move toward stabilization, the economy was dollarized and a Global Political Agreement (GPA) between the two main political parties was signed in September 2008. Inflation subsequently decreased and economic growth retuned, although headwinds are evident[1].

[1] http://www.worldbank.org/en/news/press-release/2016/02/03/economic-headwinds-in-2016-could-challenge-zimbabwes-achievements-since-stabilization.

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Land and access to it has been a central policy focus throughout Zimbabwe's history. At Independence in 1979, the country had 33 million hectares of arable farm land, but about 45% of it was owned by fewer than 10,000 white farmers. As a part of Independence negotiations, the Lancaster House Agreement was signed on the 21st of December in 1979. The agreement outlined a process to redistribute land from white European Zimbabweans to blacks. Land reform officially began in 1980 and during the 1980s, land re-distribution occurred on a willing buyer, willing seller basis. By the end of the 1980s, donors, who had provided the reserves for the purchase of lands, became weary and the pace of reforms slowed (Moyo, 2011). Unhappy with the pace of land reform and beginning in 2000, landless blacks (many of whom were veterans of the independence struggle) began to invade white-owned farms. As a response to these invasions, government began implementing a fast track land resettlement program. Government acquired most of the invaded farms and resettled the invaders. Subsequently, more than 3,100 farms were distributed among 214,340 black farmers (Mabaye, 2005). Our survey data sets show that in 2001, 2007, and 2011, 84%, 86% and 87%, respectively, of rural households owned a piece of land.

When economic conditions deteriorate, poorer households often send their children to work as a means of coping. Sending children to work instead of school leads to less human capital attainment and lower economic growth, as human capital is an important determinant of growth (Barro, 1991; Jacoby & Skoufias, 1997). Decisions about whether to send children to school or to work are affected by several factors. Many papers have argued that the main cause of child labor is poverty. Lack of resources, together with other factors such as credit constraints, income shocks, school quality, and parental attitudes toward education are all associated with child labor (Ersado, 2005; Jacoby & Skoufias, 1997; Weir, 2011). Additional explanations for child labor are presented by Cigno and Rosati (2005).

Ignoring rare cases of parents who do not feel benevolent toward their children, parents prefer not to send their children to work if they can afford not to. This axiom, proposed by Basu and Van (1998), is called the luxury axiom and is generally assumed in the literature on child labor. There is much evidence to support the luxury axiom (Basu, 1999; Basu & Tzannatos, 2003; Edmonds, 2005; Emerson & Souza, 2003; Ersado, 2005; Ray, 2000). But other evidences challenge the argument that poverty is the main cause of child labor. Bhalotra and Heady (2003) show that child labor increases with household land ownership in Ghana and Pakistan. Since land ownership is strongly correlated with household incomes and wealth in rural areas, they question the presumption that child labor is characteristic of the poorest households. Authors have dubbed this seeming anomaly "the wealth paradox" (see also Dumas, 2007; Duryea & Arends-Kuenning, 2003; Edmonds & Turk, 2004; Francavilla, Giannelli, & Grilli, 2013; Friebel, Leinyuy, & Seabright, 2015; Islam & Choe, 2013; Kambhampati & Rajan, 2006; Kruger, 2007; Sarkar & Sarkar, 2016).

The land/child labor relationship is complex. Land has two opposing effects (income and substitution) on child work and parental investments in human capital. On the one hand, the amount of land (or any other productive asset such as livestock, capital in a family enterprise, etc.) available to the household affects the productivity of the children and consequently affects incentives for putting children to work on the farm (substitution effect). In the absence of a smooth labor market, the productivity of a child laborer increases with landholding; therefore, demand for the child work raises. On the other hand, more land is associated with higher incomes, which decreases demand for child work and increases demand for schooling/leisure (income effect). Therefore, how child work changes with a household's landholding is an empirical question. Does the income effect or the substitution effect dominate? Does one of the effects always dominate or is the pattern of the dominance nonlinear?

It may seem that an easy and efficient way to reduce poverty in rural areas is to give productive assets (agricultural capital) to poor people. Such a policy prescription assumes that the income effect dominates, but the literature has found important counter examples. For example, Cockburn and Dostie (2007) study theoretically and empirically the relationship between child labor and a wide range of child labor demand factors including household productive assets in the context of rural Ethiopia. They show that asset-based poverty reduction policies can provoke rural households to withdraw their children from school in order to work with the assets.

We show theoretically and empirically, using nationally representative household surveys from various years in Zimbabwe, that the relationship between child labor and a household's land holding per capita is neither linear nor quadratic, but instead rather like a cubic function, with an upward bump in the middle of a generally downward-sloped relationship.

We theorize that the bump in the downward relationship between land holdings and child labor is caused by two factors, one associated with household preferences and the other with changes in productivity. First, the value of a child's education (the disutility of putting children to work) increases with wealth. The wealthier the household, the more valuable is education of children. Second, holding household labor fixed, when land size increases the marginal product of a child worker increases.

Following Basu, Das, and Dutta (2010), we assume that labor markets are quite imperfect. This assumption is justified because workers find it difficult and exhausting to work on others' land, and employers may prefer not to hire non-family workers due to moral hazard and high supervision costs. Moreover, most parents feel apprehensive about sending their children to work in distant factories or farms due to security concerns (Foster & Rosenzweig, 1994, 2004; Jacoby, 1993; Jayaraj & Subramanian, 2007). In fact, the data show that only 0.96% of children work out of family across all three years in Zimbabwe.

When a household with small amounts of land puts many workers in its fields, the marginal product of additional workers will be low. As holding size increases, the marginal product of labor increases. When holding size is very large, the marginal product increases at a decreasing rate and it finally reaches a limit. This limit exists because if the amount of land is great enough, some land will remain unused, because there will be insufficient household labor to cultivate the fields, and in the absence of a labor market, non-family workers cannot be hired. Therefore the incentive for putting children to work on farms, which comes from the gap between the marginal product of the child and the marginal return to education, changes in a complex way as land size increases.

This discussion does not apply only to rural households; it applies to any household with productive assets (wealth). For example, a productive wealth in urban areas can be in form of owning a shop. As a result, a similar analysis can be applied to urban households.

Different factors affect the productivity of a child on farm (e.g. the productivity of land). In farming areas where rainfall is higher and soil quality is better, the income effect of the land is larger (more land is associated with higher farm incomes in high-quality areas compared to low-quality areas), so child labor can be lower, holding other factors fixed, in high-rainfall areas. On the other side, the productivity of the child on farm is higher in such areas; incentives for putting the child to work can be stronger in areas with favorable agro-ecological conditions. It will be shown that incentives for putting children to work for very poor households are stronger in wet areas (more productive) than in dry areas, and also it will be shown that equal increments in wet land owned, holding other factors constant, leads to sharper declines in child labor in comparison to dry land owned.

The bump in the relationship between holding size and use of children on the farm has an important implication from the perspective of policy making. Both very poor households and households with medium-sized holdings are likely to have high incidences of child labor, so policy makers wishing to reduce child labor should focus on both classes of farms. The former group would be excluded if the relationship between child labor and wealth were presumed to have an inverted U shape like Basu *et al.* (2010). The latter group would be excluded if poverty were thought to be the sole cause of child labor. In addition, as seen in the empirical results it is possible that households who hold small amounts of land are less/more likely to send their children to work than households whose land holding is in an intermediate range. The results suggest that the pattern of association between child labor and land holdings can change over time; policy makers should be aware of this shifting relationship. This relation can be affected by the gender of the child or agro-ecological conditions.

To evaluate our theory empirically, we normalize landholdings by the number of available workers and focus on land holding per household member of working age. Data come from three nationally representative household surveys conducted by Zimbabwe's National Statistical Agency (ZIMSTAT) in urban and rural areas of Zimbabwe in 2001, 2007/8, and 2011/12. These surveys contain information on household demographics, schooling, healthcare, employment and household enterprises, asset ownership, consumption expenditures and income.

Our paper is similar to Dumas (2013) who studied the effect of labor, land and credit market imperfections on child labor in Madagascar. She states that market imperfections cause the probability of being a child laborer to rise; however the effects are heterogeneous across land ownership. She sorts the households into four quartiles based on land holdings and assumes that households in quartiles one and three behave as if they faced imperfect markets, while households in quartiles two and four behave as if they faced competitive markets. Her theory predicts an M-shaped curve for the supply of child labor versus land holding, but she finds an S-shaped curve, which is similar to our results. Our theoretical analysis is based on changes in the marginal productivity of children as land size increases holding household labor supply fixed. Therefore, in our empirical analysis, household labor is fixed. Dumas (2013) does not treat the labor pool as fixed. When we relax the assumption of a fixed household labor pool, we no longer get an S-shaped curve, but when it is fixed, the S-shaped curve emerges. We include a 4^{th} degree polynomial of land in our regressions to see whether find an M-shaped curve as her theory predicts, but we were unable to reproduce the theoretical patterns observed in her paper.

Theory is presented in Section 2, the empirical results are discussed in Section 3, and the conclusions are stated in Section 4.

2. Theory

The theoretical section rests on three assumptions. First, following Basu *et al.* (2010), we suppose that the labor market is quite imperfect. Basu *et al.* (2010) explain that labor markets are usually quite imperfect in developing countries (Foster & Rosenzweig, 1994, 2004; Jayaraj & Subramanian, 2007). The assumption of an imperfect labor market seems to be valid because workers may find it difficult and exhausting to work on others' land and employers may prefer not to employ non-family workers due to moral hazard and high supervision costs.

Before explaining the next assumption, we introduce the following notation. Consider a farm household that owns K units of land and has one adult who always works regardless of leisure (consuming no leisure) and a single child. The maximum amount of labor supply by each individual is normalized to one hour; therefore, the amount of labor supply by the adult is equal to one hour. Denote amount of work done by the child as $L_c \in [0, 1]$; then $1 - L_c$ shows the amount of hours spent on education. Therefore, $L = 1 + L_c$ is labor employed on the land[2]. Suppose the household produces $q(L, K)$ units of output, whose price is normalized to one. Then the production function is only a function of labor and land (capital).

We now introduce the second assumption. Households are benevolent toward their children, that is, putting children to work has a negative effect on utility. Let $\varphi(L_c)$reflect the disutility associated with child labor and assume it to equal $(cK + a)L_c$, where c. and a are positive constants. That is, wealthier households receive more disutility from putting children to work instead of sending them to school (recall that K represents the household's land holding (wealth)). In other words, we assume that the value of education is higher for wealthier households. Therefore, the value of education at each level of K can be shown by $(cK + a)(1 - L_c)$. As a result, the marginal value of time spent educating children is $cK + a$.

The third assumption is about the changes of the marginal productivity of labor ($q_L(L, K)$) as land holding increases. Basu *et al.* (2010) assume that $\partial(q_L)/\partial K = q_{LK} > 0$, that is, the marginal productivity of labor increases with land size. Many other papers make the same assumption (e.g. Dumas, 2013). There are many other factors that affect the productivity of labor such as the adoption of new vintage of capital and more productive cultivation processes. However, for the sake of simplicity of the model, we only consider the land size and assume that the marginal productivity of labor increases with land size.

When land size is very large, equal increments of land results in smaller and smaller increments in the marginal productivity of labor. After a threshold, land size becomes very large and some land is unused. Unused land emerges because, first, the labor market is assumed to be quietly imperfect, so more labor cannot be hired for the unused land. Second, the number of workers is fixed, and labor becomes thinly spread and nothing is produced on the unused portion. At this point, the productivity of labor approaches a constant.

Consider a farm household with the following utility function and budget constraints:

$$U = U(C, L_c) = u(C) - \varphi(L_c) \; s.t. \; C = q(K, L) \tag{1}$$

Suppose $u(C) = C$ and $\varphi(L_c)$, which reflects the disutility of sending children to work, was already assumed to be equal to $(cK + a)L_c$, where c and a are positive constants. By substituting $u(C)$, C and $\varphi(L_c)$ into (1):

$$U = q(K, L) - (cK + a)L_c = q(K, L) - (cK + a)(L - 1) \tag{2}$$

The household maximizes its utility (2) with respect to L:

$$\max_L \; q(K, L) - (cK + a)(L - 1) \tag{3}$$

We study interior solutions. The first-order condition is:

$$\frac{\partial q}{\partial L} - (cK + a) = 0 => q_L(K, L) = cK + a \tag{4}$$

[2] In reality the child's productivity is less than that of adults, therefore we must have $L = 1 + \beta L_c$, where $\beta \in (0, 1)$ is a constant representing the lower productivity of the child. For simplicity, we assume that $\beta = 1$. This assumption does not affect the model's outcome. If we want to include this fact that children are less productive than adults into the empirical analysis, we should multiply the number of children by a factor less than one. To calculate the factor empirically, we should compare the wages of children who work out of family with those of the adults; however, first, there are a few children who have stated that they work out of family, second, most of them have not reported their income. Therefore, we cannot calculate the factor.

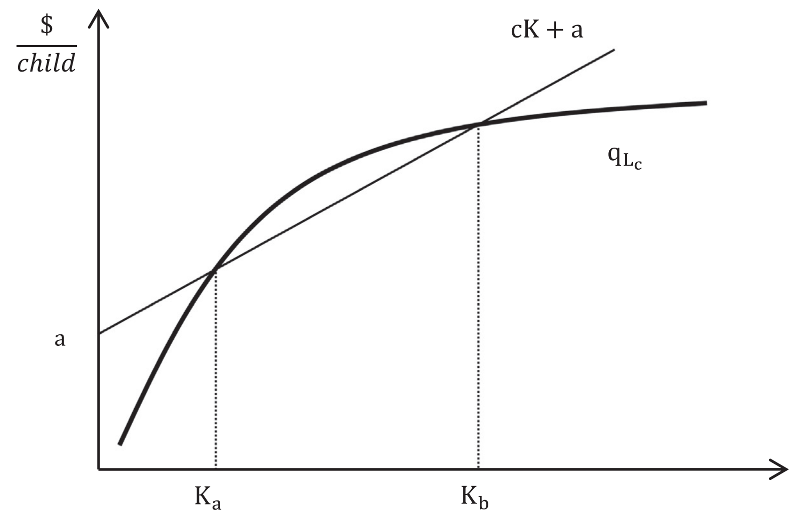

Figure 1. Marginal productivity of child labor and expected marginal value of education.

By the second order condition, we have $q_{LL}(K, L) < 0$. Therefore, if $cK + a > q_L$, the labor supply L falls, and if $cK + a < q_L$, labor supply L increases.

We now compare the marginal productivity of a child and his/her marginal value of education (marginal cost/disutility of working). The marginal value of education is $cK + a$ (MV_{edu}– reflected by the straight line in Figure 1). By the third assumption, the marginal productivity[3] of children on the farm is represented by the solid curve in Figure 1.

Compare the marginal productivity of the child with the marginal value of education. When land size rises from zero, $cK + a$ is larger than q_L up to K_a; therefore, labor supply L falls. In other words, child labor supply L_c falls (recall $L = 1 + L_c$). After K_a, when land size increases, $cK + a$ is smaller than q_L up to K_b; therefore, child labor supply L_c increases. Finally, when K passes K_b, again $cK + a$ is larger than q_L; therefore, child labor supply L_c falls.

To summarize, our theory shows clearly the following outcomes of an increase in household landholding:

- When holding size is small ($K < K_a$), child labor decreases as holding size increases.
- When it is intermediate ($K_a < K < K_b$), child labor increases as holding size increases.
- When holding size is large ($K_b < K$), child labor decreases as holding size increases.

These outcomes are shown graphically in Figure 2. As we see, in the absence of a labor market, children work for their own family, therefore the magnitude of the marginal productivity of children in comparison to their expected return to education plays a key role in the probability of being sent to work instead of the school. Landholding is one of the key factors that affect the productivity of child; however, there are some other factors such as the demographic composition of the household (see, Cockburn & Dostie, 2007).

3. Empirical analysis

(a) Data

Three nationally representative household surveys conducted by ZIMSTAT are employed for the analysis. The Incomes, Consumption and Expenditure Surveys (ICES) were conducted from January 2001 to January 2002 and from June 2007 to December 2007. The 2007/8 ICES survey was intended to be conducted from June 2007 to May 2008, but, because of the economic crisis, it was not completed and a few observations were collected in 2008. The Poverty, Incomes, Consumption and Expenditure Survey (PICES), using an identical questionnaire, was conducted from June 2011 to May 2012. There are 12806, 11615 and 25052 surveyed households respectively in 2001, 2007 and 2011, in rural areas[4]. These surveys use similar sampling designs and questionnaires and are representative at the provincial and higher levels. Our analysis focuses on households in rural areas.

(b) Variables

We introduce two dependent variables to represent child labor. A question in the questionnaire asks: Has (name) ever attended school? Answers are: (1) never been; (2) at school; and (3) left school. If a child has left school, then there is another question which asks about the reason. If a child aged 7–14 has never gone to school or has left school and this leaving is not because of illness then he/she is considered to be a child laborer.

This definition has some limitations. First, in developing countries, if a child is in school and also works more than a specific amount of time, he/she may be considered to be a child laborer. Unfortunately, there is no question about the amount of work done

[3] In reality, there is a distribution of the marginal productivity of labor and the return to education. That is, productivity and returns are not known by decision makers with certainty. They vary across households at a given level of landholding due to unobserved factors such as the fertility of land and the quality of school, etc. However, the inclusion or exclusion of the distributions do not affect the outcome of the model. Therefore, for the sake of clarity and the simplicity of the model the distributions are not included to the model. Suppose the curved and the straight lines show, respectively, the expected productivity and returns to education across households at a given level of landholding.

[4] About one percent of the households who are among top two percent of land owners, stated that they do not own any assets (even a radio or bicycle). Obviously, these observations represent mis-measurement and are dropped. Most of these same households have not answered other questions as well.

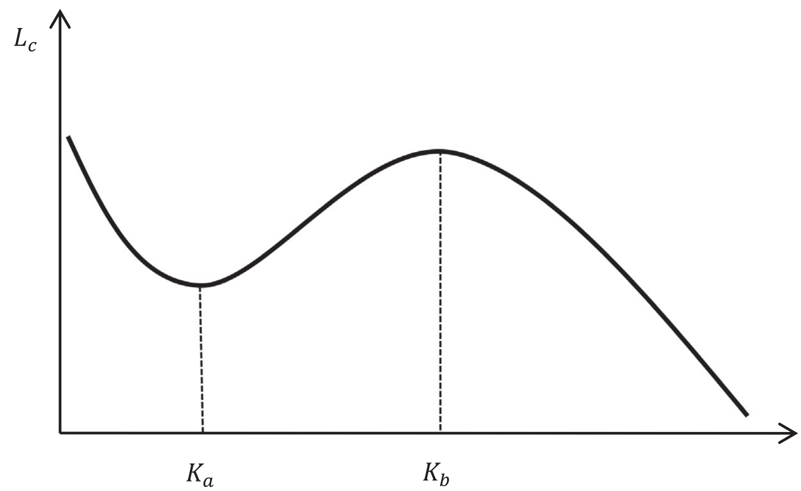

Figure 2. Child labor vs. land holding.

by each individual in the questionnaire. Because of this lack of information, if a child works and goes to school at the same time, we consider the child to be in school (not a child laborer). We give priority to education. Schooling represents a possibility of earning more in the future. In addition, many children in rural areas routinely contribute to work on the farm before and after school. It would not be proper to consider these children as child laborer. Since our interest is in examining tradeoffs between wealth and investments by households in their children's education, we do not consider children who go to school and also work.

Second, it is possible that a child does not go to school and also does not work, but it is highly unlikely that a child who drops out of school (or has never gone to school) does not work and consumes leisure in rural areas of less-developed countries. This limitation may cause a logical concern about very poor households. They might not have any land to put their children to work, and also cannot afford to send their children to school.

If a household does not hold any land, the family members may work in others' land, and put their children in home to do domestic chores. Hazarika and Sarangi (2008) show that the probability of being a child laborer increases as household access to microcredit increases; because, the adults are busy in their enterprises and children have more domestic chores. The data show that there are 450 children across all three years who are not in school and their households hold no land. The main activity of 266 of them was recorded. 189 children are classified as either homemakers or unpaid family workers, 40 are either employees or own account holders, 19 are unemployed, and 18 do other activities. As can be seen, 71% of them are working for their family. Note that this explanation contradicts the assumption of the absence of the labor market. The assumption was made for the simplicity of the theoretical model, and in reality, there should be a limited labor market in most rural areas of less-developed countries.

Another survey question asks about the main activity of each individual during the past 12 months. We use this question to define our alternative dependent variable. This definition relies on a question about the main activity of each family member during the past 12 months. If the main activity of a child aged 7–14 is working[5], then he/she is considered as a child labor. This alternative definition does not have the limitations of the first dependent variable, but about 40 percentage points of the children who answer the previous question about being or not being in school have not answered this question. Therefore, our sample size is much smaller when child labor is defined based on the main activity of the child.

In the theory section, we analyzed the changes of the marginal product of labor when land size increases, while labor size is fixed. That is, one of the factors of production (here, labor) is fixed, and the other one (here, land) varies. However, the problem is that in the empirical section, each household has a different labor size. Therefore, we need to normalize households such that all have the same labor size. Therefore, we need to divide the land size by the number of workers. In this way, we can fix the labor size, and study the effect of land. However, dividing the land size by the number of workers leads to some problems[6]. We can only divide the land size by the number of family members above six years old (L). In this way, the independent variables of primary interest, K/L, $(K/L)^2$ and $(K/L)^3$, are constructed. Other variables are listed in Table 1 with their definitions and summary statistics.

Four categories of responses related to land holding are available in the survey: (1) Total hectares; (2) own hectares; (3) hectares loaned/rented out during the last 12 months; and (4) hectares rented/borrowed in the last 12 months. Total available land is likely to be endogenous to the child labor decision because it includes rented and sharecropped land. However, the amount of rented land is small, reflecting less than two percent of total land, on average, across the surveys. This finding is likely to reduce the problem of endogeneity, but may not solve the problem.

[5] A question asks: What was (name's) main activity in the last 12 months? Possible responses are: Paid employee, Employer, Own account worker, Unpaid family worker, Unemployed, Student, Homemaker, Retired, Other. If the main activity of a child is not "unemployed" or "student", then he/she is considered to be a child laborer.

[6] We explain by an example why land size is divided by the number of individuals more than six years old. Suppose two households (A and B) both have one hectare, three adults, and one child whose age is between 7 and 14. Suppose the child of family A works and that of B does not work. Now, if land is divided by the number of working individuals, then the independent variable is 1/4 in family A and 1/3 in family B, so less land per worker is associated with a higher probability of having a working child, in other words, K/L is correlated negatively with the probability of being a child laborer. For solving this problem, you may want to divide land by four (household size), but there will still be another problem. Suppose family B has a child who is younger than seven. If land is divided by household size, then the independent variable is 1/4 in family A and 1/5 in family B, while it must not be different. Because both households have the same amount of land, they need to the same amount of workers, but a child who is less than seven is too young to work in the field. Such children should not be reflected in the land holding variable. Therefore, we divide land (K) by the total number of individuals in the household who are more than six years old (L).

Table 1
Definition of variables and descriptive statistics

Variable	2001	2007	2011	Definition
CL_school	0.07 (0.25)	0.10 (0.29)	0.06 (0.23)	The first dependent variable. A dummy variable equal to one if a child aged 7–14 has never gone school or has left school, and zero otherwise
CL_activity	0.07 (0.25)	0.10 (0.31)	0.07 (0.25)	The second dependent variable. A dummy variable equal to one if the main activity of a child aged 7–14 is to work during the last 12 months, and zero otherwise
Land per L	0.48 (1.70)	0.59 (5.99)	0.62 (4.70)	Amount of land holding in hectares divided by the number of individuals in household greater than six years old
Asset Index	0.40 (0.21)	0.26 (0.28)	0.39 (0.26)	Asset Index divided by household size. The index is calculated using Multiple Correspondence Analysis
Tractor	0.01 (0.12)	0.01 (0.12)	0.02 (0.13)	A dummy variable equal to one if the household own a tractor or has a free access to it
Age	20.91 (18.53)	21.62 (18.78)	21.54 (19.24)	Age of child
Male	0.47 (0.50)	0.48 (0.50)	0.48 (0.50)	A dummy variable equal to one if a child is male, and zero otherwise
Head male	0.60 (0.49)	0.63 (0.48)	0.64 (0.48)	Equal to one if head is male and zero otherwise
Head age	48.77 (14.47)	49.06 (15.29)	49.19 (15.43)	Age of head of household
Head education	0.20 (0.40)	0.31 (0.46)	0.43 (0.49)	A dummy variable equal to one if head has received at least a primary school certificate and zero otherwise
Siblings	0.41 (0.70)	0.36 (0.64)	0.35 (0.63)	The number of siblings in school who are 15–25 years old
Males < 7	0.64 (0.81)	0.61 (0.80)	0.63 (0.79)	Number of males in household six years old and younger
Females < 7	0.64 (0.81)	0.60 (0.77)	0.63 (0.78)	Number of females in household six years old and younger
School age	2.17 (1.63)	2.05 (1.57)	2.04 (1.54)	Number of children in school age
Primary	3.14 (10.7)	3.54 (16.25)	3.36 (21.30)	Distance to primary school in km
Secondary	6.81 (6.03)	6.12 (14.91)	5.94 (16.92)	Distance to secondary school in km

Notes: Mean values are shown with standard deviations in parentheses.

Land owned is used since there is good reason to think it is exogenous to the child labor decision and is widely used in the literature (Bhalotra & Heady, 2003; Lima, Mesquita, & Wanamaker, 2015). Land is usually inherited and land markets are undeveloped in Zimbabwe, where customary tenure still predominates. Land transactions are limited by a weak land market in developing countries (Bali Swain, 2001; Rosenzweig & Wolpin, 1985). In our data, only four, two, and 24 households in 2001, 2007, and 2011, respectively, report selling or buying land. We thus consider owned land to be exogenous[7]. In 2001, 2007, and 2011, 84%, 86% and 87% of rural households reported owning land.

We also control for asset wealth using an asset index. Multiple correspondence analysis was used based on ownership of the following assets: House tenure status (own, tenant, lodger, tie), water (river, borehole, communal tap, piped outside, piped inside), cooking fuel (gas, electricity, wood, ...), toilet (none, Blair, flush, pit), access to electricity, juice extractor, toaster, food mixer, washing machine, electric heater, stove, motor vehicle, refrigerator freezer, bicycle, television, radio, telephone and sewing machine. This asset index reflects the non-productive household wealth and controls for income effects not related to land and farm productivity.

(c) Estimated equation

The vector of characteristics of the ith child is denoted by X_i and household characteristics are denoted by X_h. D_j is a dummy variable for district j, which controls for unobservable local fixed effects. Suppose X shows the vector of all independent variables. That is, $X = \{X_i, X_h, D_j\}$. The dependent variable y_{ihj} is a dummy variable equal to one if the ith child in the hth household residing in district j is out of school. If the utility of sending a child to work (U_w) is higher than the utility of sending the child to school (U_s), then $y_{ihj} = 1$, unless $y_{ihj} = 0$. It can be shown that:

$$\begin{aligned} Pr(y_{ihj} = 1|X) &= \Pr(U_w - U_s > 0|X) \\ &= F(\alpha + X_i\beta_1 + X_h\beta_2 + D_j\beta_3 + \epsilon_{ihj}) \end{aligned} \quad (5)$$

where $F(z) = e^z/(1+e^z)$ for a logit model. The logit model is separately estimated using 2001, 2007 and 2011 data. Key variables are K/L, $(K/L)^2$ and $(K/L)^3$, elements of X_h. After running regressions, we examine the graph of the probability of a working child versus land size per worker to test whether Figure 2 is supported empirically.

(d) Empirical results in different years

Estimation results of the regression of child labor on K/L, $(K/L)^2$ and $(K/L)^3$ are reported in Tables 2 and 3 for two different dependent variables of child labor defined based on school attendance (Table 2) and main activity during the past 12 months (Table 3). Errors are clustered at the household level, and unobservable district fixed effects are included[8]. The first four columns present the log of the odds ratios and the last four columns show marginal effects at the means. In the first column all three years of data were pooled and the regression was run on pooled data set. In the 2nd, 3rd, and 4th columns results from separate regressions are shown for the 2001, 2007, and 2011 samples, respectively. For the sake of brevity, we analyze only the coefficients of per capita land (productive wealth) and the asset index divided by household size (unproductive wealth).

In addition to the per capita land and the asset index, all regressions include a constant, the number of males and females less than seven years old, the number of siblings in school, the number of children in schooling age, age and gender of child, head's age, gender, and education, distance to primary school and secondary school, tractor ownership, and unobservable district fixed effects. In the first column, two dummy variables for years 2001 and 2007 are also included.

[7] It might be thought that land invasions in 2000 may pollute the exogeneity of land owned, but the amount of occupied lands was small relative to total land available. Most invasions occurred in provinces Mashonaland East (97 farms were occupied out of 1430 farms), Mashonaland West (41 farms were occupied out of 1680 farms) and Masvingo (66 farms, but we do not know the total number of the farms in this province). Matabeleland North and South, Manicaland and Midlands experienced a few occupations. In addition, consider that the government began implementing a fast track land resettlement program immediately after the invasions. The government acquired most of the occupied farms, and also gave 2900 white farmers three months to vacate their farms. Their lands were acquired by government, and then 3,178 farms, which were acquired from both whites and invaders, were redistributed among 214,340 Black farmers (Mabaye, 2005; Marongwe, 2002; Moyo, 2011).

[8] The errors were clustered at the level of district as well, and similar results were found. We prefer to cluster at the level of household since agro-ecological conditions change considerably across Zimbabwe.

Table 2
Log of Odds ratios and marginal effects from the regression of child labor (defined based on school) on land/L using a logit model, 2001, 2007, 2011, pooled all three years

	Log(Odds)				ME			
	Pooled	2001	2007	2011	Pooled	2001	2007	2011
Asset index	−2.307***	−2.615*	−1.694*	−3.540***	−0.149***	−0.162*	−0.137*	−0.177***
	(−3.79)	(−1.72)	(−1.66)	(−4.72)	(−3.80)	(−1.72)	(−1.67)	(−4.67)
Land/L	−1.391***	−3.329***	−1.189***	−1.308***	−0.044***	−0.081***	−0.051***	−0.030***
	(−5.74)	(−4.34)	(−2.92)	(−3.98)	(−5.58)	(−4.13)	(−3.06)	(−3.83)
$(Land/L)^2$	1.050***	4.207***	0.775**	0.995***				
	(4.69)	(3.45)	(2.25)	(3.19)				
$(Land/L)^3$	−0.195***	−1.498***	−0.137*	−0.177**				
	(−3.78)	(−2.77)	(−1.87)	(−2.50)				
Tractor	−0.130	−0.323	−0.182	−0.224	−0.008	−0.018	−0.015	−0.010
	(−0.64)	(−0.81)	(−0.48)	(−0.90)	(−0.67)	(−0.93)	(−0.48)	(−0.99)
Primary	0.001	0.003	−0.002	0.001	0.001	0.000	−0.000	0.000
	(0.99)	(1.42)	(−0.65)	(1.52)	(0.99)	(1.42)	(−0.65)	(1.52)
Secondary	0.001	0.013**	0.003	−0.001	0.001	0.001**	0.000	−0.000
	(0.41)	(2.06)	(1.19)	(−0.64)	(0.41)	(2.06)	(1.19)	(−0.64)
Age	0.147***	0.115***	0.107***	0.260***	0.009***	0.007***	0.009***	0.013***
	(11.91)	(5.52)	(4.96)	(12.31)	(12.07)	(5.51)	(4.97)	(12.84)
Male	0.232***	0.031	0.357***	0.260***	0.015***	0.002	0.029***	0.013***
	(5.13)	(0.38)	(4.46)	(3.80)	(5.15)	(0.38)	(4.45)	(3.82)
Males < 7	0.010	0.097*	−0.072	0.034	0.001	0.006*	−0.006	0.002
	(0.32)	(1.83)	(−1.21)	(0.71)	(0.32)	(1.82)	(−1.21)	(0.71)
Females < 7	0.054	0.004	0.115**	0.037	0.003	0.001	0.009**	0.002
	(1.58)	(0.06)	(2.07)	(0.73)	(1.57)	(0.06)	(2.07)	(0.73)
Siblings	−0.703***	−0.519***	−0.798***	−0.773***	−0.045***	−0.032***	−0.065***	−0.039***
	(−12.45)	(−5.70)	(−7.82)	(−7.88)	(−12.12)	(−5.72)	(−7.47)	(−7.65)
School age	0.069***	0.087***	0.058	0.056*	0.004***	0.005***	0.005	0.003*
	(3.51)	(2.71)	(1.61)	(1.92)	(3.48)	(2.68)	(1.60)	(1.91)
Head male	0.254***	0.201**	0.278***	0.174**	0.016***	0.012**	0.023***	0.009**
	(4.76)	(2.06)	(2.92)	(2.23)	(4.82)	(2.09)	(2.89)	(2.23)
Head age	0.001	0.002	−0.003	0.006**	0.001	0.000	−0.000	0.000**
	(0.54)	(0.65)	(−1.15)	(2.36)	(0.54)	(0.65)	(−1.15)	(2.34)
Head education	−0.682***	−0.326**	−0.948***	−0.595***	−0.039***	−0.019**	−0.077***	−0.027***
	(−9.66)	(−2.22)	(−7.81)	(−6.54)	(−10.87)	(−2.44)	(−7.53)	(−6.99)
Dummy for 2007	0.358***				0.025***			
	(5.59)				(5.50)			
Dummy for 2011	−0.201***				−0.011***			
	(−3.50)				(−3.43)			
Constant	−4.542***	−4.524***	−3.172***	−6.387***				
	(0.25)	(−8.93)	(−7.81)	(−17.33)				
N	55076	14098	12189	28789				
R^2	0.07	0.07	0.09	0.10				
Joint Test	0.00	0.00	0.01	0.00				

*Denotes significance at 10%, **at 5% and ***at 1%. Numbers in parentheses are *t* statistics. Errors are clustered at household. Marginal effects are calculated at means. All regressions include district fixed effects. In the first column all years are pooled and two dummy variables for years 2001 and 2007 are also included to the regression. The last row reports the *p*-values of the test of joint insignificance of the land coefficients.

Table 3
Log of Odds ratios and marginal effects from the regression of child labor (defined based on main activity) on land/L using a logit model, 2001, 2007, 2011, pooled all three years

	Log(Odds)				ME			
	Pooled	2001	2007	2011	Pooled	2001	2007	2011
Asset index	−2.153***	−0.347	−5.236***	−2.565***	−0.144***	−0.020	−0.434***	−0.147***
	(−3.15)	(−0.26)	(−3.44)	(−3.57)	(−3.15)	(−0.26)	(−3.40)	(−3.55)
Land/L	−1.043***	−2.817***	−0.975**	−0.994**	−0.032***	−0.052**	−0.043**	−0.024**
	(−3.76)	(−3.00)	(−2.09)	(−2.52)	(−3.58)	(−2.45)	(−2.29)	(−2.30)
$(Land/L)^2$	0.797***	3.983***	0.601	0.815**				
	(3.15)	(2.79)	(1.51)	(2.19)				
$(Land/L)^3$	−0.143**	−1.490**	−0.093	−0.151*				
	(−2.55)	(−2.49)	(−1.14)	(−1.79)				
Tractor	−0.044	0.143	−0.451	−0.121	−0.003	0.009	−0.039	−0.007
	(−0.18)	(0.30)	(−1.10)	(−0.42)	(−0.19)	(0.29)	(−1.13)	(−0.44)
Primary	−0.001	0.002	−0.001	−0.001	−0.001	0.001	−0.001	−0.001
	(−0.55)	(0.97)	(−0.48)	(−0.64)	(−0.55)	(0.97)	(−0.48)	(−0.64)
Secondary	0.002	0.010	0.004	0.001	0.001	0.001	0.001	0.001
	(1.13)	(1.00)	(1.23)	(0.73)	(1.12)	(1.00)	(1.22)	(0.73)
Age	0.456***	0.528***	0.373***	0.528***	0.030***	0.031***	0.031***	0.030***
	(21.09)	(12.19)	(9.90)	(17.96)	(21.18)	(11.92)	(10.13)	(17.17)
Male	0.208***	−0.124	0.393***	0.316***	0.014***	−0.007	0.033***	0.018***
	(3.70)	(−1.21)	(3.71)	(3.93)	(3.71)	(−1.21)	(3.69)	(3.98)
Males < 7	0.064	0.134*	0.093	−0.004	0.004*	0.008*	0.008	−0.001
	(1.64)	(1.89)	(1.33)	(−0.08)	(1.64)	(1.88)	(1.32)	(−0.08)
Females < 7	0.045	−0.048	0.112	0.057	0.003	−0.003	0.009	0.003
	(1.13)	(−0.66)	(1.64)	(0.94)	(1.13)	(−0.66)	(1.63)	(0.94)
Siblings	−0.904***	−0.650***	−1.042***	−0.992***	−0.060***	−0.038***	−0.087***	−0.057***
	(−11.99)	(−5.06)	(−7.58)	(−8.20)	(−11.77)	(−5.08)	(−7.32)	(−8.02)
School age	0.060***	0.051	0.083*	0.045	0.004**	0.003	0.007*	0.003
	(2.59)	(1.19)	(1.93)	(1.30)	(2.57)	(1.19)	(1.90)	(1.30)
Head male	0.213***	0.128	0.269**	0.166*	0.014***	0.007	0.022**	0.009*
	(3.33)	(1.02)	(2.29)	(1.93)	(3.35)	(1.03)	(2.25)	(1.94)
Head age	0.004**	0.008*	−0.001	0.007**	0.001**	0.001*	−0.001	0.001**
	(2.09)	(1.80)	(−0.04)	(2.26)	(2.10)	(1.80)	(−0.03)	(2.26)
Head education	−0.535***	−0.189	−0.772***	−0.467***	−0.032***	−0.011	−0.064***	−0.025***
	(−6.43)	(−1.07)	(−4.86)	(−4.45)	(−7.06)	(−1.12)	(−4.85)	(−4.67)
Dummy for 2007	0.484***				0.034***			
	(6.22)				(6.11)			
Dummy for 2011	0.017				0.001			
	(0.24)				(0.24)			
Constant	−8.718***	−9.803***	−6.939***	−9.929***				
	(0.384)	(−11.98)	(−11.22)	(−18.89)				
N	34086	8725	7378	17950				
R^2	0.12	0.12	0.14	0.14				
Joint Test	0.00	0.03	0.12	0.04				

*Denotes significance at 10%, **at 5% and ***at 1%. Numbers in parentheses are t statistics. Errors are clustered at household. Marginal effects are calculated at means. All regressions district fixed effects. In the first column all years are pooled and two dummy variables for years 2001 and 2007 are also included to the regression. The last row reports the p-values of the test of joint insignificance of the land coefficients.

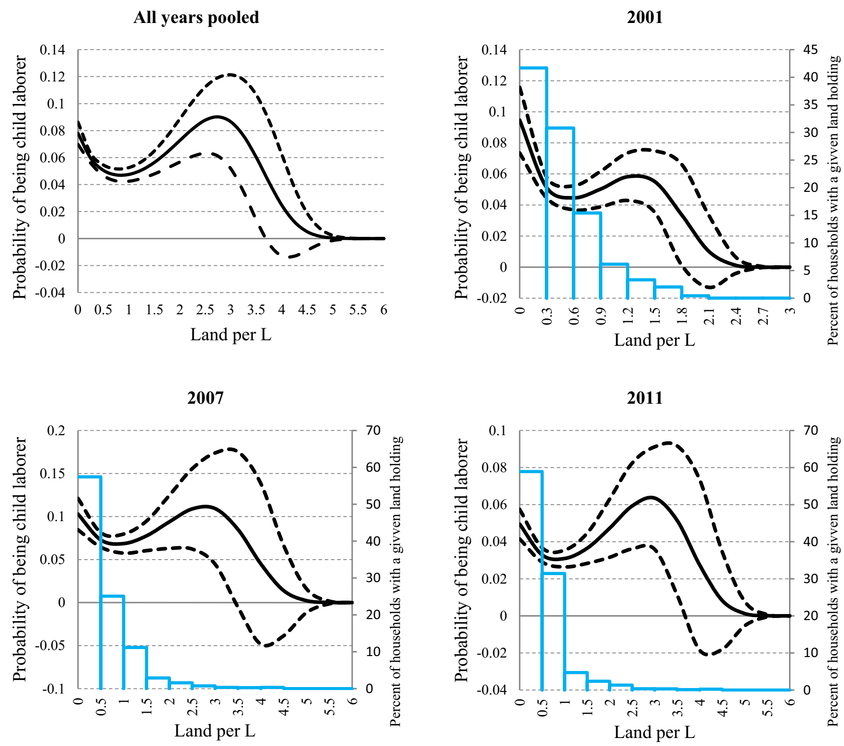

Figure 3. Probability of being a child labor (black lines) and percent of households (blue lines) vs. Land/L across all years and separately in each year, rural Zimbabwe. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The theory shows that the cubic form of the relationship between land holding and the dependent variable is the proper one; a cubic form will be consistent with the 'bump' the theory predicts. Other relationships are possible, for example, Basu *et al.* (2010) suggest the relationship is quadratic (the inverted U). To rule out competing theories, the last rows of Tables 2 and 3 report *P*-values of the test of joint insignificance of the land coefficients. In addition to the joint test, additional tests are shown in Appendix B to check the functional relationship between holding size and child labor. These tests clearly indicate that the cubic form is the relevant relationship and help validate our theory.

The coefficients of K/L, $(K/L)^2$ and $(K/L)^3$ are highly significant in both tables, and the test of joint insignificance of them is rejected in all regressions except in 2007 when dependent variable is defined based on the main activity of the child (4th column of Table 3).

The predicted values of the probability of being a working child as a function of K/L, with their 95% confidence intervals[9], are shown in Figure 3 by the black lines. This figure uses the estimated coefficients of Eqn. (5) from Table 2 (the first dependent variable). Because Table 2 contains more observations than Table 3, its results are more precise. In Figure 3, all variables are set equal to their means except per capita land holding, which varies from zero to its maximum. The blue lines show the percent of households with a given land holding as a function of *Land*/*L*.

The results of Tables 2 and 3 accompanied with Figure 3 provide empirical support for the theory presented in Section 2. As we see, the probability of putting a child to work falls as per capita land increases, while there is a bump along the way. The mean of the predicted probabilities shows that the bump begins to emerge on average around 0.6, 1.0, and 0.9 hectares per household member and it peaks on average about 1.3, 2.7, and 2.9 hectares per household member respectively in 2001, 2007, and 2011.

Figure 3 shows that when land holding is in an intermediate range, the probability of having children work on the farm is on average around 6%, 11% and 6.5% respectively in 2001, 2007 and 2011. Therefore, the probability of putting to work for the children whose households have medium land holdings increased about 5 percentage points (pp) during the shock and then fell by about 4.5 pp.

When land holding is very small, the probability of working is on average about 9.5%, 11% and 5% respectively in 2001, 2007 and 2011. Therefore, the probability increased by 1.5 pp during the crisis and then fell by about six pp.

These results suggest that incentives for putting children to work increased during the crisis for both middle and poor wealth class households, but it increased a lot more in the middle wealth class. These results are obtained because the households who own a medium-sized holding of land need the income of child in crisis and there is enough land for children to be sufficiently productive. But, incentives for child labor is lower during the crisis for households who own a small piece of land because although they may need the income of child, there is insufficient land for children to be put to work productively.

These observations are made by comparing the mean of the probability of being a child laborer in Figure 3. These estimates are not very precise, because the 95% confidence intervals (CI) are large when the amount of per capita land is large. The CIs are large because the number of households with large holdings is small; if only a few households put their children to work, the variance rises quickly and the CI grows.

We saw that poor households and households with medium-sized holdings are likely to have a high incidence of child labor, so policy makers wishing to reduce child labor should focus both on households with very small holdings and on those with medium-sized holdings. The poor group might be excluded if the relationship between child labor and wealth were assumed to have an inverted U shape like seen in Basu *et al.* (2010), and the middle group would be excluded if poverty were thought to be the sole

[9] To draw the CIs, the delta method is used (Xu & Long, 2005).

cause of child labor. Furthermore, we see in the empirical results that it is possible for households with small land holdings to be either less or more likely to send their children to work than households whose land holding is in an intermediate range. If the probability of putting children to work for very poor households is higher than those with medium landholdings in one year, it will not necessarily be the case in other years. Our results suggest that this pattern can change over time. We will see later that this result holds even for different groups of households based on their agro ecological conditions or gender of child.

In Table 2, the marginal effects of landholding show that the probability of being a child laborer decreased by 8.1 pp, 5.1 pp, and 3 pp for each additional owned hectare in 2001, 2007, and 2011 respectively. The same pattern emerges in Table 3, with this difference that the magnitude of the numbers is smaller to some extent (5.2 pp, 4.3 pp, and 2.4 pp in 2001, 2007, and 2011 respectively). The explanations of why the effect of productive wealth on child labor decisions decreased over time are left for future research.

With respect to the asset index, the log of odds ratio and ME are weakly significant in 2001 and 2007 and highly significant in 2011 when child labor is defined based on school attendance (Table 2). The log of odds ratio and ME are not significant in 2001 when child labor is defined based on main activity (Table 3), but they are highly significant in 2007 and 2011. The marginal effects are all negative, which suggest that the probability of having a child laborer decreases as unproductive wealth increases. Consider that it is impossible to compare the coefficients of the land and asset index variables because the unit (scale) of the asset index is meaningless.

(e) Empirical results for different groups

Similar patterns of the relationship between child labor and per capita land holding were found across the three different surveys and when all years were pooled. Therefore the results are robust. In this section we study the effect of agro-ecological conditions and gender of child on the probability of being a child laborer. This section introduces two enhancements to the prior analysis. First, the pattern of change in the probability of being a child laborer is similar to the prior analysis, reinforcing the notion that the prior reported results are robust. Second, different groups can be prioritized for policy makers wishing to reduce child labor (to enhance children's education).

Theoretically, factors affecting land productivity can also affect the probability of child labor through their relationship to the productivity of labor. The marginal productivity of labor can be different when land productivity changes. Due to differences in this productivity, incentives for putting children to work can differ according to local agro-ecological conditions. Soil quality, rainfall, and other factors affect land productivity. To examine the role of agro-ecology, the dataset is divided into wet and dry areas[10].

Results are reported in Table 4. We have used the first definition of child labor in Table 4, because it contains much more observations than the second definition, and as a result its estimates are more precise (recall that the number of observations is about 40 pp less when the second definition is used), and also we are interested in examining tradeoffs between wealth and investments by households in their children's education.

The first four columns contain log odds ratios, and the last four columns are MEs. All coefficients of per capita land are again highly significant. A comparison of the land and asset index coefficients shows that the effect of unproductive wealth on being a child laborer is identical in wet and dry areas, while there is a large difference between the effect of land (the productive component of wealth) in wet and dry areas. In wet areas, the probability of being a child laborer falls by 7.1 pp for each extra per capita hectare, while the probability decreases only by 1.4 pp in dry areas. The larger effect in wet areas is likely due to a larger income effect associated with favorable agro-ecological conditions in wet lands. Since productivity is higher on wet-area farms, farmers can earn more income for each additional per capita land holding in wet areas than in dry areas. Child labor decreases more for each additional per capita land holding in wet areas compared to dry areas due to this higher income effect.

We use the estimated coefficients of Eqn. (5) from Table 4 to graph the probability of putting children to work against per capita land holding (Figure 4). The same pattern is found as in Figure 3, providing additional support for the robustness of our results.

The probability of putting children to work for those who own a small amount of land and those with medium-sized holdings is, respectively, on average about 8.5% and 8.0% in wet areas, and about 6.5% and 9.0% in dry areas.

Therefore, first, by comparing poor and middle land wealth classes between areas, we understand that the poor (middle) class in wet (dry) areas is more likely to put its children to work than in dry (wet) areas by about two pp (one pp). Second, by comparing poor and middle land wealth classes within areas, we understand that in wet areas the probability of putting children to work is equal for both poor and middle classes. However, in dry areas the probability is higher for the middle class compared to the poor class. Poor households need the income that children bring with his/her work in both areas, but in dry areas when land size is small, there is limited work to do because of the low productivity of land, so the incentive for putting the children to work is lower. But, when land size is medium, there is use for labor. In wet areas, lands are more productive and the higher income effect of land means that wet-area households with medium holding sizes have fewer incentives to put their children to work.

From the perspective of policy making, it is obvious that the probability of putting children to work (leaving school) varies by agro-ecology. Therefore, policies designed to encourage schooling might differ by agro-ecology. For example, in wet (dry) areas, poor (middle-class) households can be in priority in receiving supportive programs.

Another factor which may change incentives for putting a child to work is the gender of the child. The marginal productivity of child labor on the farm may differ by gender and this difference may lead to differential use of child labor. Valuation of education may depend on gender of the child for a variety of reasons. In Zimbabwe, girls' education has been widely promoted and different measures of school enrollment have consistently been higher for girls compared to boys (Larochelle, Alwang, & Taruvinga, 2016).

We already included the gender of the child in all regressions, and found that male children are more likely to be put to work by 1.5 pp. To see the effect of gender on the probability of being a child laborer more deeply, we run two separated regressions for each gender and drop the dummy from the list of covariates. Results are reported in Table 4.

The coefficients of per capita land are highly significant in Table 4. The MEs of land in Table 4 show that for each additional per capita hectare, the probability of being a child laborer falls by approximately 4.8 pp for girls and 4 pp for boys. The MEs of the asset index show that the probability of being a child laborer falls by approximately seven pp for girls and 31 pp for boys when the asset index increases by one unit. Therefore, the productive wealth effect is relatively similar by gender, but, a large gender difference

[10] Vincent and Thomas (1960) divided Zimbabwe into five agro-ecological regions, known as natural regions on the basis of rainfall, soil quality, vegetation and other factors. Natural regions III, IV and V are considered as dry areas (in which rainfall is maximum 800 mm/year).

Table 4
Log of Odds ratios and marginal effects from the regression of child labor (defined based on school) on land/L using a logit model, different groups when all three years are pooled

	Log(Odds)				ME			
	Wet	Dry	Girl	Boy	Wet	Dry	Girl	Boy
Asset index	−2.310***	−2.909***	−1.200*	−4.406***	−0.146***	−0.191***	−0.070*	−0.311***
	(−2.93)	(−2.98)	(−1.71)	(−5.29)	(−2.94)	(−2.99)	(−1.72)	(−5.24)
Land/L	−1.881***	−0.755**	−1.518***	−1.300***	−0.071***	−0.014	−0.048***	−0.040***
	(−5.47)	(−2.24)	(−4.18)	(−4.45)	(−5.48)	(−1.62)	(−4.42)	(−4.07)
$(Land/L)^2$	1.264***	0.721**	1.064***	1.041***				
	(4.11)	(2.25)	(3.06)	(3.81)				
$(Land/L)^3$	−0.219***	−0.147**	−0.194**	−0.195***				
	(−3.21)	(−1.97)	(−2.31)	(−3.12)				
Tractor	−0.176	−0.038	−0.159	−0.106	−0.010	−0.002	−0.009	−0.007
	(−0.58)	(−0.14)	(−0.59)	(−0.35)	(−0.62)	(−0.14)	(−0.63)	(−0.36)
Primary	0.002	−0.001	0.001	0.002**	0.001	−0.001	0.001	0.001**
	(1.29)	(−0.51)	(0.38)	(1.99)	(1.29)	(−0.51)	(0.38)	(1.98)
Secondary	−0.001	0.003**	0.001	0.001	−0.001	0.001**	0.001	0.001
	(−0.66)	(2.11)	(0.34)	(0.42)	(−0.66)	(2.11)	(0.34)	(0.42)
Age	0.086***	0.214***	0.171***	0.128***	0.005***	0.014***	0.010***	0.009***
	(4.76)	(12.80)	(8.95)	(7.99)	(4.77)	(13.05)	(9.09)	(8.05)
Male	0.128*	0.339***			0.008*	0.022***		
	(1.85)	(5.91)			(1.86)	(5.89)		
Males < 7	−0.018	0.036	0.038	−0.008	−0.001	0.002	0.002	−0.001
	(−0.34)	(0.89)	(0.87)	(−0.19)	(−0.34)	(0.89)	(0.87)	(−0.19)
Females < 7	0.068	0.045	0.033	0.075*	0.004	0.003	0.002	0.005*
	(1.19)	(1.12)	(0.72)	(1.67)	(1.19)	(1.12)	(0.72)	(1.67)
Siblings	−0.614***	−0.800***	−0.784***	−0.640***	−0.039***	−0.052***	−0.045***	−0.045***
	(−7.59)	(−10.33)	(−8.92)	(−8.98)	(−7.39)	(−10.02)	(−8.86)	(−8.80)
School age	0.068**	0.076***	0.044	0.092***	0.004**	0.005***	0.003	0.006***
	(2.31)	(2.87)	(1.62)	(3.76)	(2.29)	(2.84)	(1.61)	(3.71)
Head male	0.206**	0.296***	0.207***	0.304***	0.013**	0.019***	0.012***	0.021***
	(2.50)	(4.34)	(2.72)	(4.44)	(2.54)	(4.36)	(2.76)	(4.47)
Head age	0.002	0.001	−0.001	0.002	0.001	0.001	−0.001	0.001
	(0.74)	(0.14)	(−0.42)	(1.07)	(0.74)	(0.14)	(−0.42)	(1.07)
Head education	−0.652***	−0.680***	−0.630***	−0.717***	−0.037***	−0.039***	−0.032***	−0.044***
	(−6.12)	(−7.71)	(−5.96)	(−8.05)	(−6.87)	(−8.66)	(−6.79)	(−8.98)
Dummy for 2007	0.465***	0.258***	0.191**	0.493***	0.033***	0.018***	0.012**	0.038***
	(4.88)	(3.11)	(2.08)	(6.02)	(4.75)	(3.08)	(2.06)	(5.92)
Dummy for 2011	−0.185**	−0.205***	−0.325***	−0.083	−0.010**	−0.012***	−0.017***	−0.005
	(−2.08)	(−2.86)	(−3.98)	(−1.11)	(−2.05)	(−2.78)	(−3.85)	(−1.10)
Constant	−3.695***	−5.113***	−4.447***	−4.480***				
	(−11.61)	(−15.69)	(−12.19)	(−13.72)				
N	25088	29988	27389	27687				
R^2	0.07	0.09	0.08	0.08				

*Denotes significance at 10%, **at 5% and ***at 1%. Numbers in parentheses are t statistics. Errors are clustered at household. Marginal effects are calculated at means. All regressions include district fixed effects.

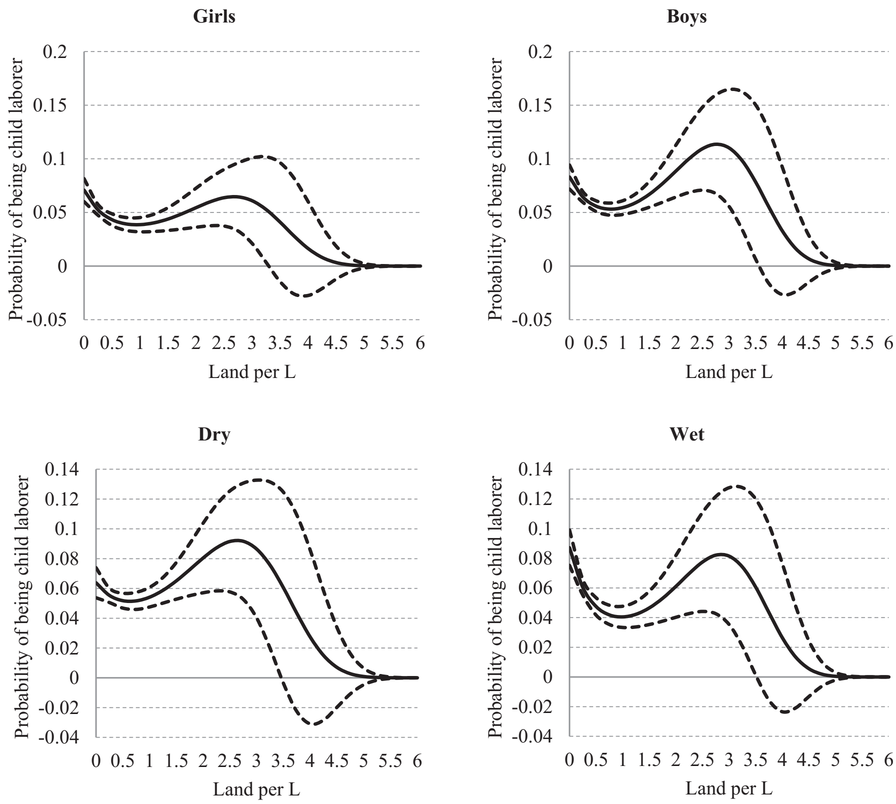

Figure 4. Probability of being a child labor vs. *Land/L* for different groups when all three years are pooled, rural Zimbabwe.

is observed by asset wealth. Boys are much more susceptible to being child laborers when non-productive wealth falls compared to girls.

Figure 4 shows that the probability of being a child laborer for girls is about seven percent and 5.5% for small-size and medium-size land owners, respectively, while the probabilities are nine percent and 11% for boys. Boys are more likely than girls to be put to work in their farms, and the probability of having a working boy (girl) is higher (lower) by about 2.0 pp (1.5 pp) when land size is medium in comparison to when land size is very small.

4. Conclusions

Many studies have shown that household wealth is an important determinant of child labor. We distinguish between productive and non-productive wealth and examine the relationship between landholding size and child labor. In this analysis it is necessary to consider that both children and land are factors of production for rural households, and changes of one of them affect the productivity of the other. So children have different productivity on farms of different sizes.

The likelihood that a household puts its children to work generally falls as land holding sizes increase, with an upward bump near the middle of the range of land per capita. The upward bump observed in this study stems from a complex relationship between the marginal productivity of child on a farm and the marginal value of his/her education at different levels of wealth, holding the quantity of labor in the household constant. Also, some small land owners are more likely to send their children to work and some medium-size land owners are as well. Findings are robust to numerous specifications of the model and indicate that it would be improper to assume that medium-sized farms are not using their children as farm workers. The economic shock experienced in Zimbabwe seems to have had a short-term effect on use of child labor. The probability of sending a rural child to work shifted upwards during the peak of the crisis in 2007, but quickly returned to a lower level. The same relationships between land holding size and the probability of child labor held in 2007, so the effect is a short-term level effect.

Productivity/wealth effects vary subtly by agro-ecological conditions and child's gender. Households with small land holdings are more likely to put children to work in wet areas (more favorable agro-ecological conditions) in comparison to dry areas and those with medium-size holdings are less likely to put their children to work in wet areas in comparison to dry areas. Boys are more likely than girls to be put to work in their household's farms, and the probability of sending a boy to work is higher when land size is medium in comparison to when it is small. The probability for girls does not vary by land size. Schooling/labor decisions for boys are much more sensitive than girls with respect to productivity and wealth.

Programs to promote school retention in rural areas should not necessarily focus only on the poorest households. Furthermore, in prioritizing different groups of a society, the policy maker should be alerted that the priority may change by some other factors such as time, gender of child, and agro-ecological conditions.

Conflict of interest

The authors declare that they have no conflict of interest.

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Appendix A

Inflation in Zimbabwe

See Table 5.

Table 5
Zimbabwe's hyperinflation

Date	Month-over-month inflation rate(%)	Year-over-year inflation rate(%)
March 2007	50.54	2,200.20
April 2007	100.70	3,713.90
May 2007	55.40	4,530.00
June 2007	86.20	7,251.10
July 2007	31.60	7,634.80
August 2007	11.80	6,592.80
September 2007	38.70	7,982.10
October 2007	135.62	14,840.65
November 2007	131.42	26,470.78
December 2007	240.06	66,212.30
January 2008	120.83	100,580.16
February 2008	125.86	164,900.29
March 2008	281.29	417,823.13
April 2008	212.54	650,599.00
May 2008	433.40	2,233,713.43
June 2008	839.30	11,268,758.90
July 2008	2,600.24	231,150,888.87
August 2008	3,190.00	9,690,000,000.00
September 2008	12,400.00	471,000,000,000.00
October 2008	690,000,000.00	3,840,000,000,000,000,000.00
14 November 2008	79,600,000,000.00	89,700,000,000,000,000,000,000.00

Source: Hanke and Kwok (2009).

Appendix B

Statistical Tests

The joint insignificance of the land coefficients in the context of a cubic polynomial was tested and shown in Tables 2 and 3. In this appendix, we test whether a cubic polynomial relation is better than a linear or quadratic one. We pool all three years of data, and run the tests for both definitions of child labor (Table 6). The results of the tests when child labor is defined based on school attendance are under the first two columns, and the last two columns are for when the child labor is defined based on the main activity of the children during the past 12 months.

To test the null hypothesis of linearity against a cubic and/or a quadratic polynomial, the null hypothesis is that the coefficients on $(\mathrm{Land}/\mathrm{L})^2$ and $(\mathrm{Land}/\mathrm{L})^3$ are equal to zero, and the alternative is that at least one of the coefficients is nonzero. Results are reported in the first row; the linear regression is rejected at the one percent level against a polynomial of degree up to three in both regressions. Therefore, a cubic/quadratic form fit the data better than a linear one.

To test the null hypothesis of a quadratic form against a cubic form, the null hypothesis is that the coefficient on $(Land/L)^3$ is equal to zero, and the alternative is that the coefficient is nonzero. The results are reported in the second row, and the null is again rejected. The null of a quadratic regression is rejected at the one percent (five percent) level against a polynomial of degree three in the first (second) regression. Therefore, a cubic form fit the data better than a quadratic one.

Table 6
Nonlinearity tests on land/L coefficients, for both child labor definitions, pooled all three years

	School attendance		Main activity	
	F-statistic	*P*-value	*F*-statistic	*P*-value
Linearity (1)	32.16	0.00	14.75	0.00
Quadratic (2)	14.24	0.00	6.44	0.01

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