Essays on Child Labor and Inequality

Ali Reza Oryoie

Dissertation submitted to the Faculty of
Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
Economics

Jeffrey Roger Alwang (Co-chair)
Nicolaus Tideman (Co-chair)
George W. Norton
Wen You

September 14, 2016
Blacksburg, Virginia

Keywords: Child Labor, Education, Inequality Analysis, Asset Index, Economic Shock

Essays on Child Labor and Inequality

Ali Reza Oryoie

ABSTRACT

This dissertation studies a number of issues related to Development Economics. The first chapter explains how we can use multiple correspondence analysis to calculate an asset index, and then offers an inequality analysis using the asset index. The second chapter provides a theoretical explanation of an odd relationship between child labor and per capita land holding in a household, and then provides empirical evidence for the explanation. Finally, the third chapter represents the results of a study of the behavior of rural households during shocks. Across the entire dissertation, we use three cross sectional surveys, conducted in 2001, 2007-8 and 2010-11 in Zimbabwe.

Essays on Child Labor and Inequality

Ali Reza Oryoie

GENERAL AUDIENCE ABSTRACT

In chapter 1, we explain an alternative for measuring household wealth to conduct poverty and inequality analysis in cases in which data on income and consumption expenditures are not available, are difficult to collect, or the data suffer from a large amount of mis-measurement.

In chapters 2 and 3 we study child labor, defined based on school attendance, in rural areas of the Zimbabwe. As reductions in child labor result in more educational attainment which is associated with higher economic growth, it is valuable to identify factors associated with use of child labor. In chapter 2, we show that both very poor households (poor based on land holdings) and households with medium-sized holdings are likely to have a high incidence of child labor. Policy makers wishing to reduce child labor should focus on both classes of households. The latter group would be excluded if poverty were thought to be the sole cause of child labor. It is even possible that small land holders might be less likely to send their children to work than households whose land holding is in an intermediate range. Intuition might say that rural children are put to work more during negative shocks (e.g. macroeconomic crisis, price fall in agricultural products, drought, pest attack, etc) and less during positive shocks in comparison to normal conditions. But we show in chapter 3 that children might be pulled out of schools during positive shocks and inverse during negative shocks in Zimbabwe, so policy makers should be worried during positive shocks and they may lower costs of education and increase incentives for keeping children in school during positive shocks by providing voucher programs and subsidies to the school.

Acknowledgements

I am very thankful my advisors, Professor Jeffrey Alwang and Professor Nicolaus Tideman, for their support, help, patience and care. I would also thank Professor George Norton, Professor Wen You and Professor Suqin Ge for their comments, helps and supports.

I would like to thank Adam Edwards and Jiangeng Huang from Virginia Tech's Laboratory for Interdisciplinary Statistical Analysis (LISA) for their input regarding the statistical method of Multiple Correspondence Analysis.

I would like to thank all of my teachers from elementary school to University for all of their endeavors and encourages.

Finally, I wish to dedicate this dissertation to my wife, parents and grandmother. Without their love, patience, support and encourage I would have never completed this endeavor.

Table of Contents

List of Figures

List of Tables

Chapter 1

Calculating Asset Index and Inequality Index using multiple correspondence analysis

1.1. Introduction

Consumption expenditures are usually considered as the best measure of living standards and are used widely for poverty and inequality analysis (Deaton, 1997). However, in developing countries data on income and consumption can be either not available or difficult to collect and such data suffers from lack of accuracy. Even seemingly innocuous changes in consumption questionnaire design can affect results of poverty/inequality analyses. Beegle, et al (2012) show how changes in consumption survey design[1] leads to big changes in both mean consumption and distributional measures using consumption surveys of six African countries (see also Lanjouw and Lanjouw, (2001), and Yu, (2008)).

An alternative for consumption expenditures or income is to use assets owned by households and calculating a wealth index. Collecting data on assets is easier, and there is less mismeasurement in data such as whether or not a household owns a house or radio than in data about consumption expenditure for each item or about income of farmers or own-account holders. In addition to these reasons, there is evidence that shows that analyses based on wealth

[1] They have studied the effects of these factors: method of data capture (diary versus recall), level of respondent (individual versus household), reference period for which consumption is reported (anywhere from 3 days to one year) and degree of commodity detail (from less than 20 items to over 400 items).

can work better than analyses based on income or consumption (Banerjee and Newman 1993; Galor and Zeira 1993; Bardhan 2000; McKenzie 2005).

Filmer and Pritchett (1998, 1999, 2001) introduced the use of principal component analysis (PCA) for constructing an asset index. PCA is a statistical method that uses the information of a large number of possibly correlated variables and converts them into a smaller set of linearly uncorrelated variables called principal components, with the specification that the first principal component captures the most common source of variation among the variables.

Following Filmer and Pritchett (2001), McKenzie (2005) used PCA for calculating an asset index, and measured relative inequality based on the index for Mexico. He calculated an asset index based on his whole sample and then divided the standard deviation of different sub-samples by the standard deviation of the whole sample to measure relative inequality in each sub-sample.

While there are many papers using PCA to calculate an asset index (for example Sahn and Stifel 2000; Filmer and Pritchett 2001; Filmer and Scott. 2012; McKenzie 2005; Patrick Ward 2014), PCA is not a good method for calculating an asset index, since assets are generally binary or categorical variables and PCA was designed for continuous variables (See Kolenikov and Angeles 2009). Some papers (Booysen et al. 2008; Echevin 2011; Asselin 2009) have used multiple correspondence analysis (MCA) for calculating an asset index, since MCA is designed for categorical variables, and it makes fewer assumptions about the distributions of variables. In PCA it is assumed that distances between categories are equal and that the categories are ordered, and these assumptions are not required in MCA (Greenacre and Blasius 2006).

Both PCA and MCA generate two clouds: of categories and of individuals. Previous studies always interpret the coordinates of the first principal axis of the cloud of individuals as an asset index. We discuss the fact that there is no theoretical reason why the coordinates of the first principal axis should represent an individual's asset index. The distance between individual points in the cloud of individuals reflects dissimilarities between asset patterns of individuals. That is, individuals who own exactly the same assets are represented by points at the same location. In contrast, the individuals who have very different assets are represented by the most distant points. This dissimilarity may come from wealth differences or it may not. For example it may come from differences in individuals' tastes, assets needed for different geographical locations, durability of goods, etc. The only way to ensure that the dissimilarity generating the first principal axis in an MCA on assets stems from wealth is to examine the coordinates of the cloud of categories and check their values and signs one by one. If the magnitudes and signs of the coordinates of the first principal axis are roughly consistent with the values of the assets, then the first dimension represents a wealth index. But if it is not a case, then we need to either modify our variables (in a way that will be explained later) or look at the coordinates of other dimensions. For example it is possible that the first principal axis reflects differences in tastes and the 2nd axis reflects wealth, in which case we need to use the coordinates of the 2nd principal axis, not the first, for making an asset index. However, looking at both previous studies and this study, it seems that the coordinates of the cloud of individuals on the first principal axis always represent the wealth level of individuals. In other words, empirically, the greatest dissimilarity among individuals (reflected on the first principle axis) comes from differences in wealth. Nevertheless, as was stated, we must be cautious and always check the coordinates of the cloud of categories one by one.

There are two other reasons for checking the signs and magnitudes of the coordinates of the cloud of categories before calculating an asset index based on them. First, even when the first principal axis represents wealth, it is possible that some of the assets bias the value of the index. For example, if all households own a house, which is the case in rural areas of most developing countries, then the sign of the coordinate of the dummy variable of owning a house will be opposite to the sign of the coordinates of other precious assets (normal goods). As an example, the sign of owning a house is negative in McKenzie (2005). In other words, owning a house under such circumstances will lead to a lower asset index. In such situations we should either drop the distorting variable or modify it (will be explained later). Second, it is possible for the sign of owning normal goods to be negative, while the sign of owning inferior goods is positive. That is, sometimes the larger the asset index, the poorer the household. In this case we must first multiply the coordinates of the cloud of categories by -1 and then calculate the asset index. It will be shown that if the signs of the coordinates are not examined, wrong results may be obtained.

It will be discussed that those variables which are composed of many categories in comparison to other variables contribute a lot more to the inequality index and bias it inappropriately. It will be explained that by combining some similar categories this problem can be solved.

In this chapter, for measuring inequality, instead of dividing the standard deviation of the asset index of different sub-samples by the standard deviation of the whole sample, we simply use the variance of the asset index as a measure of inequality, since this allows us to decompose it into between-group and within-group variances. This decomposition allows measurement of between and within group inequalities. We then test the equality of the variances in order to check the statistical significance of changes in inequality. To the best of our knowledge, previous studies that analyze inequality using PCA or MCA have not done this decomposition and the statistical test.

Our data set comes 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.

Zimbabweans have faced severe economic difficulties in the recent past. In the decade beginning in 2000 the economy was consumed by hyperinflation, falling incomes, and political instability. Inflation began to grow slowly in 1997, as people became impatient with the slow process of economic restructuring. In rural areas, veterans of the independence struggle began protesting perceived inadequacies in earlier land reform efforts, and farm invasions began in the late 1990s. These invasions had the effect of pushing land reform to the front of the policy agenda. Changes in the ownership and use of land, exacerbated by the exodus of nearly 4,500 commercial farmers, a severe drought, and a foreign exchange crisis led to food shortages. Following a downward spiral in economic conditions, Zimbabwe experienced a prolonged hyperinflation in 2007 and 2008. Teachers, health professionals and may others emigrated due in part to low real wages. 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 the recovery is still fragile (Richardson 2013).

It will be shown that inequality in the whole country increased during the economic shock and decreased afterward, but it did not return to its initial value. That is, inequality in 2011 was higher than in 2001. If we decompose the whole sample (all three years) into two sub-samples of urban and rural families, we will see that there is a considerable inequality between urban and rural families. It will be shown that inequality in urban areas increased in 2007 and then returned to its initial value in 2011, and in rural areas, in 2007, inequality was the same as in 2001, but it increased in 2011.

We will see that by decomposing the whole sample into urban and rural areas in each year, we get six sub-samples. It will be shown that inequality between urban and rural areas increased during the shock, but it returned to its initial value after the shock.

Section 1.2 explains the MCA method and calculation of a relative inequality measure. It also discusses some caveats in choosing variables before running an MCA, and disadvantages of using variance as a measure of inequality. A statistical test for the equality of variances is also discussed in this section. Section 1.3 then discusses empirical results and section 1.4 concludes.

1.2. Methods

1.2.1. Multiple Correspondence Analysis

When considering MCA, statistical software programs generally produce only the coordinates of the cloud of categories. The coordinates of the cloud of individuals (in fact we calculate the cloud of households, but in the literature the cloud is usually called the cloud of individuals) on the first principal axis are interpreted as a measures of wealth. Here we explain how the asset index can be calculated from the cloud of categories.

Suppose there are Q questions, each question has K_q categories, and in total there are K categories. Also suppose that the coordinate of the kth category on the first principal axis is denoted by y_k if the category is chosen, and K_i denotes the set of the Q categories chosen by individual i. Also suppose that the variance of the cloud of categories on the first principal axis is denoted by λ_1. The coordinate of individual i on the first principal axis of the cloud of individuals is denoted by y^i, and it is found from the cloud of categories using equation 1.1[2]:

$$y^i = \frac{1}{Q\sqrt{\lambda_1}} \sum_{k \in K_i} y_k \qquad (1.1)$$

In MCA, y^i can be interpreted as individual i's wealth, so the variance of y^i can be interpreted as a measure of inequality.

Variance as an inequality index has advantages and disadvantages (Cowell 2011). We cannot calculate another inequality index using the asset index, because MCA calculates the asset index such that its mean is equal to zero, and all of the famous inequality indices are divided by the mean, so they cannot be calculated.

If we want to compare changes of inequality over time using an MCA asset index, we must pool the data for all years and then calculate an asset index, or if we want to compare the changes of inequality across different communities, we must pool the data for all communities and then run MCA. If we don't pool and run a separate MCA for each year (community), then MCA

[2] When MCA is run in Stata, it must be typed *method(indicator) normal(principal)* as options, and then using command *predict*, Stata calculates the coordinates of the first dimension using equation (1.1).

calculates different weights (y_k and y'_k) for assets in each year (community). That is, the scale of the weights might be different.

We should be cautious in choosing variables/questions when calculating an inequality or asset index, because some variables may contribute a lot to variance and bias it inappropriately. To see how, Suppose V_{cloud} represents the summation of the variances of all principal axes. It can be shown that the contribution of question q to V_{cloud} is (Le Roux and Rouanet 2010 p. 38):

$$Ctr_q = \frac{K_q - 1}{K - Q} \tag{1.2}$$

Equation (1.2) shows that the more categories a question has, the more the question contributes to the overall variance. The larger contribution can be problematic. For example, suppose water quality includes five categories. Then, (1.2) shows, the contribution of water question to the variance of the cloud will be four times more than the contribution of owning a house, while owning a house is expected to have a closer relation to household's wealth. Therefore, questions with many inappropriate numbers of categories may bias our overall variance. But consider that it does not mean that the variance of the first principle axis will be biased necessarily. This is because (1.2) represents the contribution of question q to the overall variance (V_{cloud}) not to the variance of the first principal axis (λ_1). To the best of our knowledge there is no mathematical relationship which can show the contribution of a question to λ_1. But, since the first principal axis captures most of the overall variance, it is expected that the more a variable contributes to V_{cloud}, the more it is likely to contribute to λ_1 as well.

If we accept that the number of categories can bias our inequality index, then it may be better to construct questions such that they all have approximately the same number of categories, or we may reduce the number of the categories of some of questions if the dissimilarity between the categories does not stem from wealth differences. For example suppose water categories are: piped water inside house, piped water outside, Communal tap, Borehole and River. We may combine two categories of “Borehole” and “River” into one category, and also “piped water outside” and “Communal tap” into another one, so at the end we will have three categories instead of five. Such adjustments are case specific and depend on the context.

Another caveat in choosing variables for calculating an inequality or asset index concerns the variables whose relative frequency f_k is very large. This is explained by an example. We know that in rural areas of developing countries nearly all people have a kind of house, but most of them usually have a traditional, inadequate house, which is a sign of being poor. Moreover, poor people generally have some inexpensive assets like a radio, a bicycle, etc. We know that MCA calculates the coordinates of the individuals so that the individuals who own similar assets will be represented by some points close to each other. In contrast, the individuals who own very different assets are represented by the most distant points. Therefore, the coordinates of the individuals who own a house will be closer to the coordinates of poor people, because owning a house is correlated with owning inexpensive assets and not owning expensive assets. That is, if we consider two wealthy individuals who have the same assets, but individual A owns a house and individual B does not, the coordinates of individual A will be closer to poor people, in other words, his/her wealth index will be lower.

To solve this problem we need to either drop the problematic variables or modify and combine them with some other variables. For example, we can change the definition of owning house in this way: an individual owns a house if he/she states that he/she owns a house and also the area of the house is more than a certain amount or if dwelling type of the house is detached/semi-detached/town house not traditional/mixed. In the empirical part we will see that if we don't modify the definition of owning house, then it will bias the asset index towards being poor.

Another caveat concerns the availability of assets over time and across space. When we pool all data on assets and calculate an asset index, our initial assumption is that all people in all areas have equal access to the assets over time. For example, if there is no cell phone service in one year and there is in another year, we must exclude cell phone ownership from calculation of the asset index, unless there is dissimilarity in our data that is not coming from wealth effect. (This means also that if there is a limited amount of a particular variable in one year or in one region, while there is an abundant amount in the other year or region, it is better to exclude it from the computation of the asset index.) For this reason, we have not included some variables like ownership of cellphone, computer and satellite phone in our analysis.

1.2.2. Between-group Inequality and within-group Inequality

Calculation of between-group and within-group inequalities is straightforward. Suppose we split our sample (cloud) into G groups (sub-clouds) and we wish to calculate inequality between and within groups. Suppose V_g and $\bar{y}_g$ represent respectively the variance and mean within group g, and $\bar{y}$ represents mean of whole sample (weighted mean of $\bar{y}_g$), and n_g is the number of individuals in group g *and* $N = \sum_{g=1}^{G} n_g$ is the total number of all individuals in the sample. The variance of y_i, which is equal to λ_1, can be decomposed into between variances and within variances as below (See appendix A):

$$V_{within} = \sum_{g=1}^{G} \frac{n_g}{N} V_g \tag{1.3}$$

$$V_{between} = \sum_{g=1}^{G} \frac{n_g}{N} (\bar{y}_g - \bar{y})^2 \tag{1.4}$$

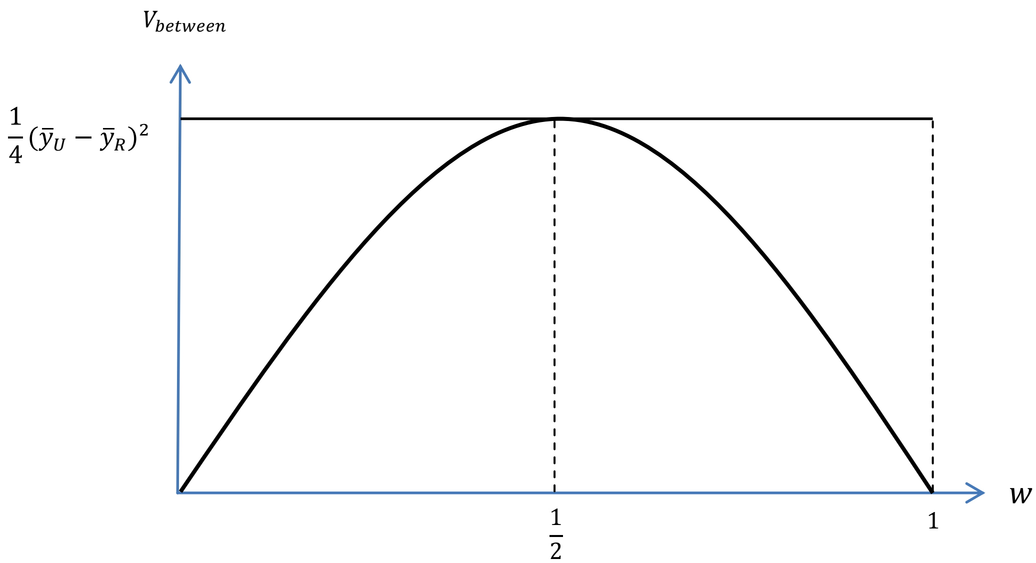
Where $V_g = \frac{\sum_{i=1}^{n_g}(y_i - \bar{y}_i)^2}{n_g}$, $\bar{y}_g = \frac{\sum_{i=1}^{n_g} y_i}{n_g}$ and $\bar{y} = \sum_{g=1}^{G} \frac{n_g}{N} \bar{y}_g$. V_{within} and $V_{between}$ are interpreted as within and between inequalities, respectively. By dividing $V_{between}$ by total variance ($V_{within} + V_{between}$), we can see what percentage of the total variance (inequality) comes from between variance (between-inequality), but $V_{between}$ may not show the actual distance between the groups well. To see why, suppose we divide a hypothetical country into groups of rural and urban and w represents the percent of the individuals who live in urban area. Also suppose each individual gets the same amount of $\bar{y}_U$ and $\bar{y}_R$ per month respectively in urban and rural areas. In this case the between-variance is:

$$\begin{aligned} V_{between} &= w[\bar{y}_U - \bar{y}]^2 + (1 - w)[\bar{y}_R - \bar{y}]^2 \\ &= (\bar{y}_R - \bar{y}_U)^2 \times (w - w^2) \end{aligned} \tag{1.5}$$

By drawing $V_{between}$ versus w holding $\bar{y}_U$ and $\bar{y}_R$ constant from (1.5), we get Figure 1.2. The between variance changes like an inverted U-shaped curve as the share of people in urban area increases from zero to one, while individuals' income is fixed, that is, the income distance between the areas has not changed.

One solution for measuring the distance between the areas is to test equality of means of the areas using t-test. The null hypothesis is that the mean of the areas are equal and alternative hypothesis is that they are not equal. If the null is rejected, then there is a significant distant between the areas.

Figure 1.2. Between variance as a function of share of urban area.



1.2.3. Statistical Test of inequality indices

To test statistical significance of changes in the inequality index across time or different areas, use a Brown, M. B., & Forsythe, A. B. (1974) test on the null hypothesis that the two groups have the same variance. We can also do an F-test (Snedecor and Cochran, 1983), but this test is very sensitive to the assumption of normality of variables, and our asset index is not normal. Therefore, we use Brown-Forsythe test since it is robust against deviations from normality and a good substitute for the F-test.

1.3. Results

In order to see inequality analysis using MCA, we use three nationally representative household surveys conducted by ZIMSTAT. 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, the 2007-8 ICES was not completed and only a few observations were collected in 2008. The Poverty, Incomes, Consumption and Expenditure Survey (PICES) was conducted from June 2011 to May 2012. These surveys use similar sampling designs and questionnaires and are representative at the provincial level. The numbers of households were 19,941 in 2001, 14,112 in 2007 and 29,765 in 2011/12.

Our variables (assets) are divided into three categories: house ownership (owner, tenant, lodger and tied), utilities (access to electricity and types of water, toilet and cooking fuel) and ownership of durable assets (electric devices, stove and some kind of motor vehicle).

Table 1.1 shows the coordinates of these variables on the first principal axis in the cloud of categories obtained using MCA. These results are found by pooling all three years of data. The first column indicates whether or not a category is owned. The second and the fourth columns show the coordinates of the cloud of categories with the difference that under the second column the definition of owning a house has not been modified (an individual owns a house if he/she has stated that he/she owns a house), while under the fourth column the definition has been modified so that an individual is defined as owning a house if he/she has stated that he/she owns a house and also that the dwelling type of his/her house is detached/semi-detached/flat/townhouse, not traditional/mixed.

Table 1.1. Coordinates of the first principal axis of the cloud of the categories, Zimbabwe, 2001, 2007, 2010-11.

	owning asset (1)	inappropriate Coordinates (2)	Effect of owning asset (3)	appropriate Coordinates (4)	−1 ×appropriate Coordinates (5)	Effect of owning asset (6)
Tenure status of house						
own	0	0.66		0.21	-0.21	
	1	-0.36	-1.02	-1.36	1.36	1.57
tenant	0	-0.02		0.02	-0.02	
	1	1.16	1.18	-1.04	1.04	1.06
lodger	0	-0.18		0.16	-0.16	
	1	1.01	1.19	-0.87	0.87	1.03
tied	0	-0.04		0.02	-0.02	
	1	0.21	0.25	-0.08	0.08	0.10
Main source of water						
river, borehole, well	0	0.92		-0.89	0.89	
	1	-0.69	-1.61	0.67	-0.67	-1.56
communal tap	0	0.02		-0.03	0.03	
	1	-0.23	-0.25	0.34	-0.34	-0.36
piped outside	0	-0.27		0.26	-0.26	
	1	0.97	1.24	-0.93	0.93	1.19
piped inside	0	-0.23		0.24	-0.24	
	1	1.48	1.72	-1.51	1.51	1.74
Cooking Fuel						
Electricity or gas	0	-0.60		0.59	-0.59	
	1	1.37	1.97	-1.37	1.37	1.96
wood, coal, paraffin	0	1.37		-1.37	1.37	
	1	-0.60	-1.97	0.59	-0.59	-1.96
Toilet						
none	0	0.28		-0.27	0.27	
	1	-0.78	-1.06	0.76	-0.76	-1.03
Blair	0	0.35		-0.35	0.35	
	1	-0.59	-0.94	0.59	-0.59	-0.95
Flush	0	-0.67		0.66	-0.66	
	1	1.20	1.87	-1.19	1.19	1.85
Other Variables						
Electricity	0	-0.71		0.70	-0.70	
	1	0.90	1.61	-0.89	0.89	1.59
Juice extractor	0	-0.02		0.02	-0.02	
	1	2.46	2.48	-2.60	2.60	2.62
Toaster	0	-0.12		0.12	-0.12	
	1	2.00	2.12	-2.08	2.08	2.20
Food mixer	0	-0.03		0.04	-0.04	
	1	2.44	2.47	-2.57	2.57	2.61
Washing Machine	0	-0.02		0.02	-0.02	
	1	2.44	2.46	-2.62	2.62	2.64
Electric heater	0	-0.15		0.16	-0.16	
	1	1.82	1.97	-1.88	1.88	2.04
Stove	0	-0.62		0.62	-0.62	
	1	1.31	1.92	-1.30	1.30	1.92
Motor Vehicle	0	-0.09		0.09	-0.09	
	1	1.60	1.69	-1.68	1.68	1.77
Refrigerator	0	-0.31		0.32	-0.32	
	1	1.56	1.86	-1.60	1.60	1.92
Bicycle	0	-0.02		0.02	-0.02	
	1	0.07	0.09	-0.08	0.08	0.11
TV	0	-0.50		0.50	-0.50	
	1	1.06	1.56	-1.07	1.07	1.57
Radio	0	-0.35		0.36	-0.36	
	1	0.39	0.73	-0.40	0.40	0.75
Telephone	0	-0.10		0.11	-0.11	
	1	1.85	1.94	-1.98	1.98	2.08
Swing Machine	0	-0.11		0.11	-0.11	
	1	0.68	0.79	-0.74	0.74	0.85

These coordinates are put into (1.1) in order to calculate the asset index, so they are like the weights of each category in the formula for the asset index. The third and sixth columns show the effect of owning an asset, which is obtained by subtracting the coordinate of not owning the asset from the coordinate of owning the asset (the sixth column is made from the fifth column, not the fourth one. It will be explained why it is made from the fifth column). But, consider that it does not show the real effect of owning an asset. To show the real effect, we need to divide the result of the subtraction by the number of the questions and the squared root of the variance of the first principle axis of the categories.

Two things are obvious from looking at Table 1.1. First, ignore the coordinates of having a house and then look at the signs of the other coordinates. When we use the coordinates of the second column, if a household is wealthy its asset index will be more positive, because the weight of having a good asset and not having a bad asset is positive and the weight of having a bad asset and not having a good asset is negative. But by the same logic we see that when we use the coordinates of the fourth column, if a household is wealthy its asset index will be more negative. Therefore, to make the interpretation of the coordinates of the fourth column more intuitive, we multiply the fourth column by -1, and report it in the fifth column, and then the sixth column is made from the fifth column. Therefore, the more positive the asset index is, the wealthier the household is. This multiplication does not change the variance of the wealth index; it only makes interpretations more straightforward.

Second, consider the coordinates of owning a house in table 1.1. A comparison of the second column and the fifth column, shows that if the definition of owning house is not modified, house ownership will reduce the asset index. But, when the definition is modified reasonably, house ownership increases the asset index. So we use the coordinates of the fifth column in our analysis.

By looking at the fifth and the sixth column we see that owning a house increases the asset index more than being a tenant or living in a lodger/tie house, we see similar results for the other variables. For example, using river, borehole or well as drinking water reduces asset index, and also using communal tap reduces the index but by less. Using outside piped water increases the index and using inside piped water increases the index but by more. These coordinates therefore suggest that the coordinates of the first principal axis of the cloud of the categories can be used for calculating the asset index in our analysis, because the magnitude of the coordinates of the categories is consistent with their values.

In Table 1.2, the variance of the asset index is calculated based on the second and the fifth columns of table 1.1. The columns whose label is appropriate (inappropriate) are calculated based on the coordinates of column 2 (column 5) in table 1.1. Both columns lead to the same result except for urban areas. As can be seen, both columns show that inequality in whole of the country increased during the shock and then decreased, but inequality did not return to its initial value. Inequality in 2011 is higher than it was in 2001. In rural areas, both columns show that inequality did not change during the shock, but after the shock inequality increased. However, in urban areas, based on appropriate coordinates, inequality increased during the shock, and subsequently it went back to its initial value, while based on the inappropriate coordinates inequality in 2011 is higher than 2001. Therefore, if we do not consider the caveats explained in section 1.2.1 regarding choosing independent variables, we may get wrong results.

Table 1.2. Variances (Inequality indices), rural and urban, multiple years.

	Whole of country		Urban		Rural	
	Inappropriate var.	Appropriate var.	inappropriate var.	Appropriate var.	inappropriate var.	appropriate var.
2001	0.29	0.29	0.13	0.15	0.06	0.06
2007	0.33	0.33	0.16	0.18	0.06	0.06
2011	0.30	0.30	0.14	0.15	0.09	0.08

Wrong and correct variances are calculated, respectively, based on the second and the fifth

In Table 1.3 we see the results of Brown and Forsythe's test. The null hypothesis is that the absolute deviations from the median of two different years are equal. For example, we saw that inequality (variance) in 2011 is larger than 2001. To test statistically whether inequality in 2001 is equal to 2011, we drop observations in 2007, and then test the null hypothesis that the absolute deviations from the median in 2001 are equal to the absolute deviations from the median in 2011. If the null is rejected, then we cannot conclude that inequality in 2001 is equal to 2011.

In Table 1.3, first, the test is done in whole of country, then in only urban areas, and finally in only rural areas. As can be seen, all of the null hypotheses are rejected except in the last row, which is reasonable because the variance in 2001 and 2007 are equal in rural areas.

Table 1.3. Brown and Forsythe's test, different areas, multiple years.

Whole of country	Statistic	P-value
2007 and 2011	1387.62	0.00
2001 and 2011	1164.74	0.00
2001 and 2007	174.45	0.00
Urban		
2007 and 2011	199.13	0.00
2001 and 2011	431.32	0.00
2001 and 2007	1108.52	0.00
Rural		
2007 and 2011	1289.57	0.00
2001 and 2011	1621.79	0.00
2001 and 2007	0.12	0.72

The null hypothesis is that the absolute deviations from the median of two different years are equal

We are interested in knowing how inequality has changed between areas (urban/rural), among years, between different areas over time, and finally among years in each area. For decomposing inequality indices (variances) we use equations (1.3) and (1.4).

The total variance of the asset index using the appropriate asset weights over all years and areas is 0.31. When the total variance is decomposed into urban and rural variances, between-area inequality is 0.21 and within-area inequality is 0.1, so between-inequality is more than twice that of within-inequality. Therefore most of the overall inequality comes from differences between urban and rural areas, not from inequality within the areas. We can test whether the between inequality is statistically significant or not using t-tests.

In Table 1.4, we have done seven different t-tests for the equality of mean of different groups of households. The null hypothesis is that the means of two different groups are equal, and this null is tested against two one-sided hypothesizes. We report only P-values for each alternative test. A_i shows mean of the asset index in group i.

As can be seen in the first test of Table 1.4, the distance between the means of the asset index in urban and rural areas is statistically significant, and people are wealthier in urban than in rural.

If we decompose the total variance into three sub-groups based on years, then within-variance is 0.3064 and between-variance is 0.0003, so most of inequality comes from variations within each year not from variations among years. The tests 5-7 in Table 1.4 show that the distance between the years is statistically significant. The results suggest that on average people got poorer in 2007, but they got wealthier after that in 2011, although not as much as 2001.

Now consider what happens when the total variance is decomposed into six sub-groups based on years and areas. We already saw that inequality between urban and rural area is large over all three years. Now, if we calculate inequality between rural and urban in each year separately, it is equal to 0.20, 0.22 and 0.20 respectively in 2001, 2007 and 2011, so inequality between urban and rural increased during the shock, but it returned to its initial value in 2011. To see whether the distances are significant, let's return again to Table 1.4. As can be seen in tests 2-4, the distance between the rural areas and the urban areas is always significant and the urban households are wealthier.

Table 1.4. One sided t-tests for equality of means of assets

Hypothesizes	P-values	Hypothesizes	P-values
Test 1		**Test 5**	
$H_0: A_{Rural} - A_{Urban} = 0$		$H_0: A_{2007} - A_{2011} = 0$	
$H_1: A_{Rural} - A_{Urban} < 0$	0.00	$H_1: A_{2007} - A_{2011} < 0$	0.02
$H_1: A_{Rural} - A_{Urban} > 0$	1.00	$H_1: A_{2007} - A_{2011} > 0$	0.98
Test 2		**Test 6**	
$H_0: A_{Rural} - A_{Urban} = 0$ in 2001		$H_0: A_{2001} - A_{2011} = 0$	
$H_1: A_{Rural} - A_{Urban} < 0$	0.00	$H_1: A_{2001} - A_{2011} < 0$	1.00
$H_1: A_{Rural} - A_{Urban} > 0$	1.00	$H_1: A_{2001} - A_{2011} > 0$	0.00
Test 3		**Test 7**	
$H_0: A_{Rural} - A_{Urban} = 0$ in 2007		$H_0: A_{2001} - A_{2007} = 0$	
$H_1: A_{Rural} - A_{Urban} < 0$	0.00	$H_1: A_{2001} - A_{2007} < 0$	1.00
$H_1: A_{Rural} - A_{Urban} > 0$	1.00	$H_1: A_{2001} - A_{2007} > 0$	0.00
Test 4			
$H_0: A_{Rural} - A_{Urban} = 0$ in 2011			
$H_1: A_{Rural} - A_{Urban} < 0$	0.00		
$H_1: A_{Rural} - A_{Urban} > 0$	1.00		

P-values are related to one-sided t-tests

1.4) Conclusion

In conducting analysis of wealth and inequality using asset indices, it is important to choose and define variables correctly. Before running MCA, it is important to have a solid understanding of the underlying assets and their contribution to wealth. Substantial effort may be required to verify that the signs and magnitudes of the estimated asset coordinates are consistent with local conditions. Some variables may need to be modified or even excluded. Then we explained how to decompose an asset-based index of inequality into between and within inequalities, and also a test of statistical significance of changes in the inequality index was developed.

It was shown that inequality in whole of the country increased during the shock and after that decreased, but it did not return to its initial value. We also saw that on average people got poorer in 2007, but they got wealthier after that in 2011, although not as much as 2001.

It was shown that between-inequality between urban and rural areas were twice as much as within inequality, and urban households were wealthier than rural households across all years.

It was shown that inequality between urban and rural increased during the shock, but it returned to its initial value after the shock. We saw that during the shock, in rural areas inequality was the same as before the shock, but it increased after the shock. And in urban areas, inequality increased during the shock, but it returned to its initial value after the shock.

Chapter 2

Child labor and household land holding: Theory and empirical evidence from Zimbabwe

2.1. Introduction

Child labor is common around the world, particularly in developing countries. In 2010, sub-Saharan Africa (SSA) had the highest rates of working children, with more than 50 percent of children aged 5–14 in several countries being employed. SSA is the poorest region of the world, and it also has the youngest population (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. The majority of working children in SSA are involved in agriculture. These children are frequently employed by their parents (International Labour Organization 1996; Edmonds and Pavcnik 2005). 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 one of SSA countries where achievements in schooling are particularly noteworthy (Larochelle, Alwang and Taruvinga 2014). Achievements in education and 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 many ways more severe than those of a typical developing country. In the decade beginning in 2000 the economy was consumed by hyperinflation (see appendix A for the magnitude of the hyperinflation)). Economic Problems led to widespread suffering and emigration of professional workers including teachers and nurses. After a long period of relative stability since Independence in 1980, inflation began to grow in 1997 due mainly to fiscal imbalances. Following a prolonged downward spiral in economic conditions, the country experienced a severe hyperinflation in 2007 and 2008 (Hanke, Kwok 2009). 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 increasing[3] (Richardson 2013).

Land and access to it has been a central policy focus through Zimbabwe's history. At Independence in 1979, there were 33 million hectares arable farming land, and about 45 % of it was owned by only 6000 white farmers. An agreement was signed on the 21th of December in 1979 whose purpose was to redistribute land equally between black farmers and white European Zimbabweans. This agreement was called Lancaster House Agreement. Land reform officially began in 1980 and since then, several redistributive reforms have taken place (Moyo 2011). Unhappy with the pace of reform and beginning in 2000, landless blacks (veterans of the independence struggle) began to invade white owned farms. Soon after the onslaught of the invasions, government began implementing a fast track land resettlement program. They acquired most of the invaded farms and resettled the invaders; they gave 2900 white farmers 3 months to vacate their farms. Subsequently, more than 3,100 farms were distributed among

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

214,340 black farmers (Mabaye 2005). Our surveyed data sets show that respectively in 2001, 2007 and 2011, 84%, 86% and 87% 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 (Jacoby and Skoufias 1997; Barro 1991). 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 and Skoufias 1997; Weir 2011).

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 is an axiom, proposed by Basu and Van (1998). It is called luxury axiom and is generally assumed in the literature. There is much evidence to support it (Edmonds 2005; Edmonds and Pavcnik 2005; Basu 1999; Ray 2000; Basu and Tzannatos 2003; Emerson and Souza 2003; Ersado 2005). But there is other evidence that 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 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; Menon 2005; Kruger 2007; Kambhampati and Rajan 2006; Edmonds and Turk 2004).

Basu, Das and Dutta (2010) have shown that the relationship between child labor and land holding is a quadratic function, and its curve has an inverted U shape. They note that child labor tends to increase with wealth (land holding) when wealth is low and then decreases when wealth is high. They explain that most parents feel apprehensive about sending their children to work in distant farms. When land ownership increases beyond a meager amount, children can work on their own farms, doing what their parents earlier wished they could do. But beyond a certain level of wealth the household will be well-off enough that it no longer puts children to work. Thus as family wealth grows, after a threshold, the probability that children are sent to work decreases.

When considering the possibility that the main cause of child labor is poverty, we may encounter difficulties if we interpret the amount of land owned as wealth, since the amount of land available to the household affects the productivity of its children and consequently affects incentives for putting children to work on the farm. We will 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 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 as wealth increases. The wealthier the household, the more valuable the education of the children becomes. Second, holding household labor fixed, when land size increases the marginal product of a child worker changes in a complex way.

Following Basu *et al* (2010), we assume that labor markets in developing countries are imperfect. This assumption is justified because workers 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. Moreover, most parents feel apprehensive about sending their children to work in distant factories or farms (Jayaraj and Subramanian 2007; Foster and Rosenzweig 1994, 2004; Jacoby, 1993).

When a household with little land puts many workers in its fields, the marginal product of additional workers will be low, since there will be little for them to do. As holding size increases, the marginal product of labor increases, initially at an increasing rate. Beyond an inflection point, 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. 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 value of education, changes in a complex way as land size increases.

There are different factors that can affect the productivity of a child on farm (e.g. the productivity of land). In those areas where rainfall is higher and soil quality is better, from one side income effect of land is higher, so child labor can be lower, and from another side the productivity of child on farm is higher, therefore incentive for putting children to work can be higher. It will be shown incentive for putting children to work for very poor households is higher in wet areas than in dry areas, and also it will be shown that equal increments in wet land owned leads to sharper decline 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 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 former group would be excluded if the relationship between child labor and wealth were presumed to have an inverted U shape. The latter group would be excluded if poverty were thought to be the sole cause of child labor. We will see in the empirical results that it is possible that the households who do not hold any land be less/more likely to send their children to work than the households whose land holding is in an intermediate range. Our 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.

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. Our data set comes 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.

Theory is presented in section 2.2, the empirical results are discussed in section 2.3, and the conclusions are stated in section 2.4.

2.2. Theory

The theory is comprised of two parts. In part a, we explain how the probability of putting children to work on a farm changes as household land holding changes. In part b, we propose a specific CES production function in support of part a.

2.2.1. Child labor analysis

Consider a farm household that owns K units of land and has one adult who always works (consuming no leisure) and a single child. Let the amount of work done by the child be denoted by $\mathrm{L_c} \in [0,1]$, so $\mathrm{L} = 1 + \beta \mathrm{L_c}$ is the labor employed on the land, where β is a constant number $\beta \in (0,1)$ representing the fact that the child's productivity is less than that of adults. Suppose the household produces $\mathrm{q(L, K)}$ units of output, whose price is normalized to 1.

Labor markets are usually imperfect in developing countries (Jayaraj and Subramanian 2007; Foster and Rosenzweig 1994, 2004). 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. Moreover, most parents will prefer not to send their children to work in distant farms or factories.

Let the household's utility function and budget constraints be:

$$U = U(C, L_c) = \mathrm{u(C)} - \varphi(L_c) \quad s.t.\ C = q(K, L) \tag{2.1}$$

Suppose $\mathrm{u(C)} = C$ and $\varphi(L_c) = (cK + a)L_c$, where c and a are positive constants. $cK + a$ reflects the disutility of sending the children to work. We have assumed that this disutility increases with land size, because it is expected that education is a normal good (Bergstrom (1986); Garratt and Marshall (1994); Benabou (1994); Pauly (1967)) and wealthier households receive more disutility from putting their children to work instead of sending them to school. This disutility is reflected in the model by multiplying K by the constant c. By substituting C into the utility function, we get:

$$U = q(K,L) - (cK + a)L_c = q(K,L) - (cK + a)\frac{L-1}{\beta} \tag{2.2}$$

The household maximizes its utility (2.2) with respect to L:

$$\max_L \; q(K,L) - (cK + a)\frac{L-1}{\beta} \tag{2.3}$$

The first-order condition is:

$$\frac{\partial q}{\partial L} - \frac{cK + a}{\beta} = 0 \quad => \quad q_L(K,L) = \frac{cK + a}{\beta} \tag{2.4}$$

Taking total differentials with respect to K and L we get:

$$\frac{\partial q_L}{\partial L} dL + \frac{\partial q_L}{\partial K} dK = \frac{c}{\beta}\, dK \tag{2.5}$$

By rearranging (2.5):

$$dL = \frac{\frac{c}{\beta} - q_{LK}}{q_{LL}} dK \tag{2.6}$$

From Eq. (2.4), we know that, for a given level of K, say K_0, the household chooses L_0 such that $q_L(K_0, L_0) = \frac{cK_0 + a}{\beta}$ and $\mathrm{q_{LL}}(K_0, L_0) < 0$ (the second-order condition). Now suppose the household's land size increases differentially ($dK > 0$). To see how child labor changes as land size increases, we need to determine the sign of dL from Eq. (2.6) evaluated at (K_0, L_0). Because $dL = d(1 + \beta L_c) = \beta dL_c$, the signs of dL and dL_c are the same.

The sign of the denominator is negative due to the second order condition, which means that producers (here our households are behaving like producers) produce on the diminishing part of the marginal productivity (q_L) curve.

Therefore, to find the sign of dL we only need to know the sign of the numerator, so we need to see how $\frac{\partial}{\partial K}\frac{\partial q}{\partial L} = q_{LK}$ changes. Basu *et al*. (2010) assume that $\frac{\partial}{\partial K}\frac{\partial q}{\partial L} = q_{LK} > 0$, that is, the marginal productivity of labor increases with land size. We make the same assumption and examine q_{LK} more deeply.

We know that $\frac{\partial}{\partial K}\frac{\partial q}{\partial L}$ represents the change in the marginal productivity of labor caused by the last unit of K (here, the last hectare), and we want to know how this changes as K increases, holding other factors constant (here, labor). When land size K is small and we increase it, holding the number of workers constant, equal increments of land size result in larger and larger increments in the marginal productivity of labor. Because when the amount of land is small, there is little for the workers to do. As land size increases, additional workers interrupt each other less and there is more for them to do, so the marginal productivity of labor increases progressively. In other words, $\frac{\partial}{\partial K}\frac{\partial q}{\partial L}|_{L=L_0}$ increases as K increases (shown graphically in the parts of Figure. 2.1 and Figure. 2.2 where $K < K_c$).

However, when land size is very large, equal increments of land result in smaller and smaller increments in the marginal productivity of labor. Because, land is very large and some parts of the land are unused (remember the number of workers is constant), the marginal productivity increases at a decreasing rate. In other words, $\frac{\partial}{\partial K}\frac{\partial q}{\partial L}|_{L=L_0}$ falls as K increases (shown in Figure 2.1 and Figure 2.2 where $K > K_c$).

In part b, we will show that $\frac{\partial}{\partial K}\frac{\partial q}{\partial L}|_{L=cte}$ of a CES production function behaves like Figure 2.1 under certain conditions.

Figure 2.1. q_{LK} vs. land size holding labor size fixed

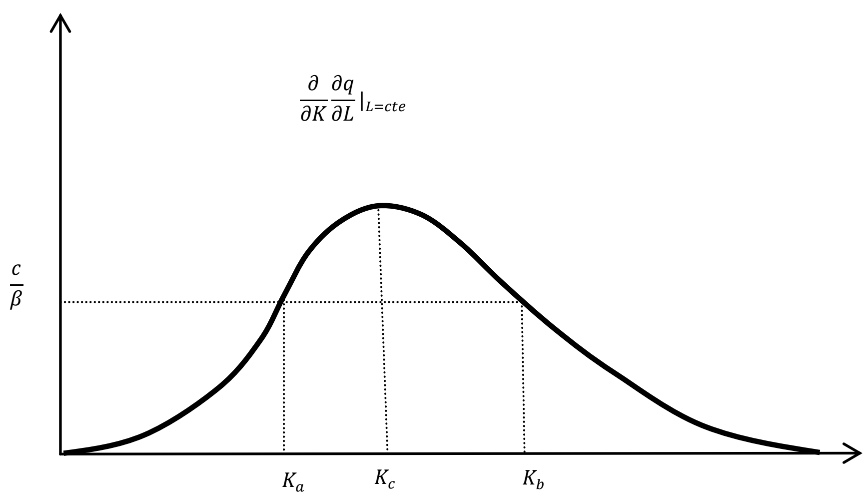
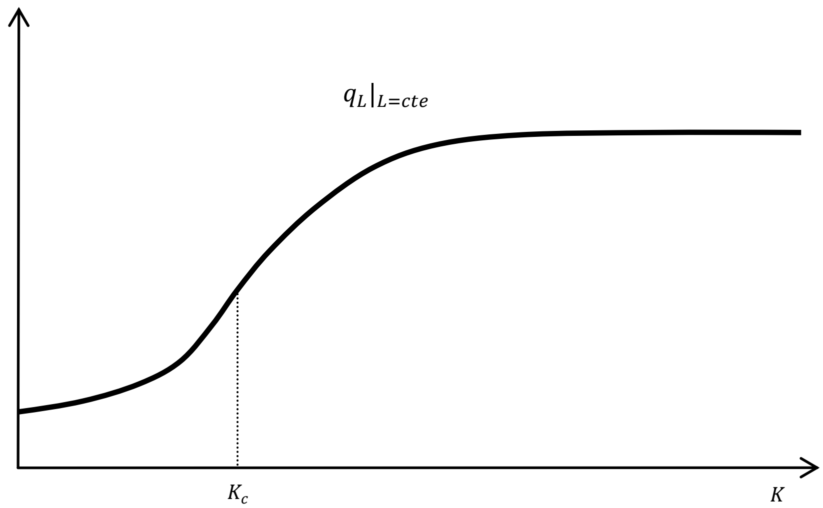


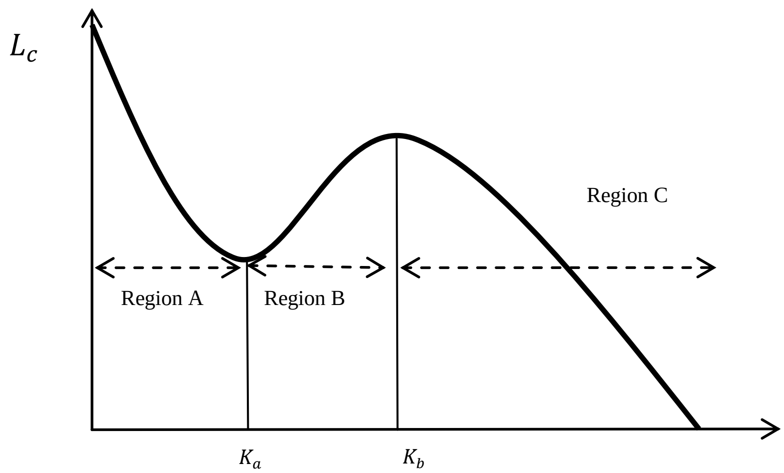
Figure 2.2. Marginal productivity of labor vs. land size holding labor size fixed



If we accept that $\frac{\partial}{\partial K}\frac{\partial q}{\partial L}|_{L=cte}$ versus K is an inverted U-shaped curve or a bell-shaped curve like Figure 2.1, then we can show that in an imperfect labor market, child labor falls as K increases holding L constant, but the decline is not monotonic; there is a bump along the way.

Using Figure 2.1 recalling that $q_{LL} < 0$, we understand when K_0 is low ($K_0 < K_a$), $\frac{c}{\beta} > q_{LK}$, so the numerator of (2.6) is positive, so $dL < 0$ (L falls or in other words L_c falls). When K_0 is in an intermediate range ($K_a < K_0 < K_b$), the numerator is negative, so $dL > 0$ (L_c rises), finally, when K is large($K_b < K_0$), the numerator is again positive, so $dL < 0$ (L_c falls). Therefore, Figure 2.3 which shows changes in $L_c = \frac{L-1}{\beta}$, can be drawn for different values of K.

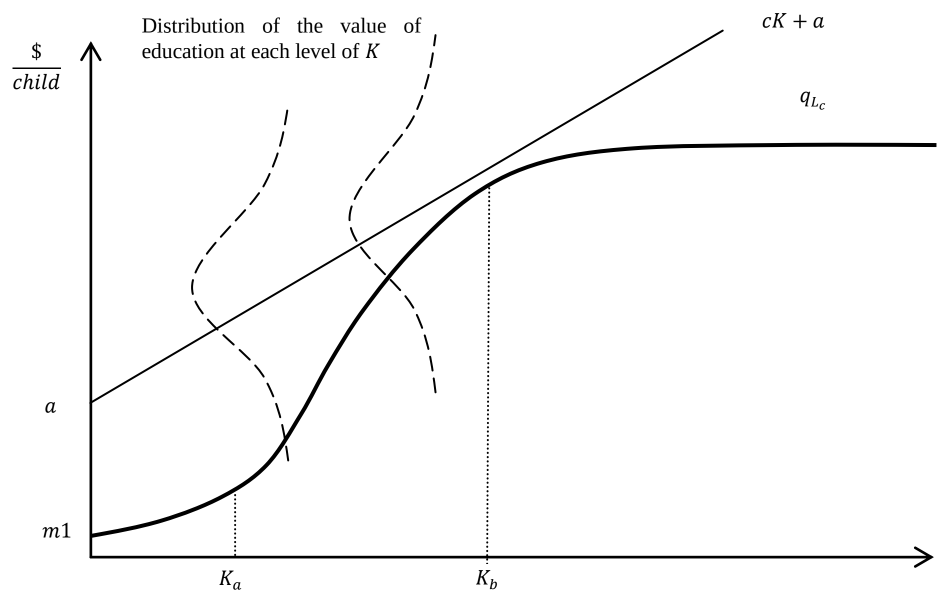
Figure 2.3. Child labor vs. land holding



We can derive Figure 2.3 graphically, without any need to calculate Eq. (2.6) or other equations, by comparing the marginal productivity of a child and his/her marginal cost of working (marginal value of education).

We explained that marginal cost of sending children to work (the marginal value of sending the children to school) is assumed to be $cK + a$. (reflected by the straight line in Figure 2.4). This cost (value) should be interpreted as the average across households at a given level of wealth, with a distribution like the vertical long dashed curves in Figure 2.4 at each level of K.

Figure 2.4. Marginal productivity of child labor and mean of marginal value of education.



Examine the marginal productivity of children on the farm, represented by the solid S-shaped curve in Figure 2.4. Patterns of changes in the marginal productivity of child labor should be similar to the change in marginal productivity of labor; because, $L = 1 + \beta L_c$, so $\frac{\partial q}{\partial L_c} = \frac{\partial q}{\partial L}\frac{\partial L}{\partial L_c} = \beta\frac{\partial q}{\partial L}$, therefore q_{L_c} in Figure 2.4 should be similar to q_L in Figure 2.2.

We can now compare marginal productivity of the child (solid S-shaped curve) with the marginal value of schooling (Solid straight line; $cK + a$). When land size rises from zero, the vertical distance between the marginal value of schooling and the marginal productivity of the children on the farm increases, up to K_a, where the slope of the marginal value line is equal to the slope of a straight line tangent to q_{L_c}. As this occurs, a progressively smaller part of the lower tail of the distribution of the marginal value of schooling falls below q_{L_c}. In other words, value of schooling to the household exceeds the value of working for a larger and larger share of households as K increases up to K_a, so child labor falls when K increases, up to K_a.

After K_a, when land size increases, the mean distance between the marginal value of schooling and the marginal productivity of the child on the farm falls, up to K_b (where the slope of the marginal value line is equal to the slope of a straight line tangent to q_{L_c} at K_b). This implies that a larger and larger part of the lower tail of the distribution of the marginal value of schooling will be below q_{L_c} as land size increases. In other words, the value of working exceeds the value of schooling for a larger and larger share of households as K increases up to K_b, so child labor increases when K increases from K_a to K_b. Finally, after K passes K_b, the distance between q_{L_c} and $cK + a$ increases again, so by the same logic child labor decreases. Therefore, the graphical analysis produces the same result as the analysis of Eq. 2.6.

In summary we have the following outcome 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

2.2.2. CES production function

We now demonstrate that the above conditions are quite plausible using a common production function—the constant-elasticity-of-substitution (CES) production function. Consider the following CES production function:

$$q = A.[\sigma.K^{\rho} + (1-\sigma).L^{\rho}]^{\frac{\epsilon}{\rho}} \quad ; A > 0\,, 0 < \sigma < 1\,, \epsilon > 0\,, \rho \leq 1\,, \rho \neq 0 \qquad (2.7)$$

Where A, σ, ϵ and ρ are all constant numbers. We will show that if $\rho < 0$ and $\epsilon > 1$, then q_{LK} as a function of K for a given positive value of L is an inverted U-shaped curve.

The marginal productivity of labor for this production function is:

$$q_L = L^{-1+\rho}\epsilon(1-\sigma)(L^\rho(1-\sigma)+K^\rho\sigma)^{-1+\frac{\epsilon}{\rho}} \tag{2.8}$$

Taking the differential with respect to K:

$$q_{LK} = K^{-1+\rho}L^{-1+\rho}\epsilon\left(-1+\frac{\epsilon}{\rho}\right)\rho(1-\sigma)\sigma(L^\rho(1-\sigma) + K^\rho\sigma)^{-2+\frac{\epsilon}{\rho}} \tag{2.9}$$

If the slope of q_{LK} with respect to K is positive when K is small and negative when K is large for any given positive L, then q_{LK} as a function of K is an inverted U-shaped curve like Figure 2.1. The derivative of q_{LK} with respect to K is:

$$\frac{\partial q_{LK}}{\partial K} = K^{-2+2\rho}L^{-1+\rho}\epsilon\left(-2+\frac{\epsilon}{\rho}\right)\left(-1+\frac{\epsilon}{\rho}\right)\rho^2(1-\sigma)\sigma^2(L^\rho(1-\sigma)+K^\rho\sigma)^{-3+\frac{\epsilon}{\rho}} + K^{-2+\rho}L^{-1+\rho}\epsilon(-1+\frac{\epsilon}{\rho})(-1+\rho)\rho(1-\sigma)\sigma(L^\rho(1-\sigma)+K^\rho\sigma)^{-2+\frac{\epsilon}{\rho}} \tag{2.10}$$

By factoring, rearranging and dropping positive terms we get:

$$\frac{\partial q_{LK}}{\partial K} \propto (\epsilon-\rho)[K^\rho\sigma(\epsilon-\rho-1) + L^\rho(1-\sigma)(\rho-1)] \tag{2.11}$$

By the definitions of parameters we know that $1-\sigma > 0$ and $\rho - 1 < 0$, so the sign of the second term in the brackets is negative. But the signs of $\epsilon - \rho$ and $\epsilon - \rho - 1$ are undetermined.

If $\rho < 0$ and $\epsilon > 1$, then both $\epsilon - \rho$ and $\epsilon - \rho - 1$ are positive. In this case, firstly, $lim_{K\to 0} K^\rho = \infty$, so the first term in the brackets, which is positive, dominates the second term for any given positive L, therefore $\frac{\partial q_{LK}}{\partial K} > 0$ when K is very small for any given positive L. Secondly, $lim_{K \to \infty} K^{\rho} = 0$, so the second term in the brackets, which is negative, dominates the first term for any given positive L, therefore $\frac{\partial q_{LK}}{\partial K} < 0$ when K is very large for any given positive L. Therefore, q_{LK} as a function of K is an inverted U-shaped curve like Figure 2.1. In this example it is like a bell-shaped curve.

It can be easily shown that if $\rho > 0$ or $0 < \epsilon \leq 1$, q_{LK} as a function of K will not be a bell-shaped curve.

We draw graphs of CES production function, q_L, q_{LK} and child labor using an example when $\rho < 0$ and $\epsilon > 1$. For example suppose $\rho = -5$, $\epsilon = 1.5$, $A = 1$ and $\sigma = 0.5$. The CES production function is:

$$q = \frac{1}{(\frac{0.5}{K^5} + \frac{0.5}{L^5})^{0.3}} \tag{2.12}$$

And marginal productivity of labor is:

$$q_L = \frac{0.75}{(\frac{0.5}{K^5} + \frac{0.5}{L^5})^{1.3} L^6} \tag{2.13}$$

Output as a function of K and L is as Figure 2.5, and q_L as a function of K for $L = 1$ is as the red line in Figure 2.7.

Suppose the distribution of the marginal value of education at each level of K follows a normal distribution with a variance equal to 1 and a mean of $\mu = 0.1 + 1.1K$ at each level of land holding. Then the mean of the distribution is like the blue line in Figure 2.7.

The cumulative density function of a normal distribution is:

$$Pr(X < x) = \frac{1}{2}(1 + erf(\frac{x - \mu}{\sigma\sqrt{2}})) \tag{2.14}$$

Here X represents marginal value of education, therefore $\Pr(X < q_L)$ shows the percentage of the households who send their children to work at each level of K:

$$\begin{aligned} \Pr(X < q_L) &= \frac{1}{2}\left(1 + \operatorname{erf}\left(\frac{q_L - \mu}{1 \times \sqrt{2}}\right)\right) \\ &= 0.5 - 0.39 \operatorname{erf}(0.1 - \frac{0.75}{\left(0.5 + \frac{0.5}{K^5}\right)^{1.3}} + 1.1K) \end{aligned} \tag{2.15}$$

By drawing $\Pr(X < q_L)$ as a function of K we get Figure 2.8, which is the percentage of the households who send their children to work as a function of land holding, for a given L, in this example $L = 1$. So as we saw, if $\rho < 0$ and $\epsilon > 1$, the probability of putting children to work on a farm falls as land holding increases for a given L, but there is a persistent upward bump near where land holding is in the middle of its range.

Figure 2.5. CES product as a function of land and labor

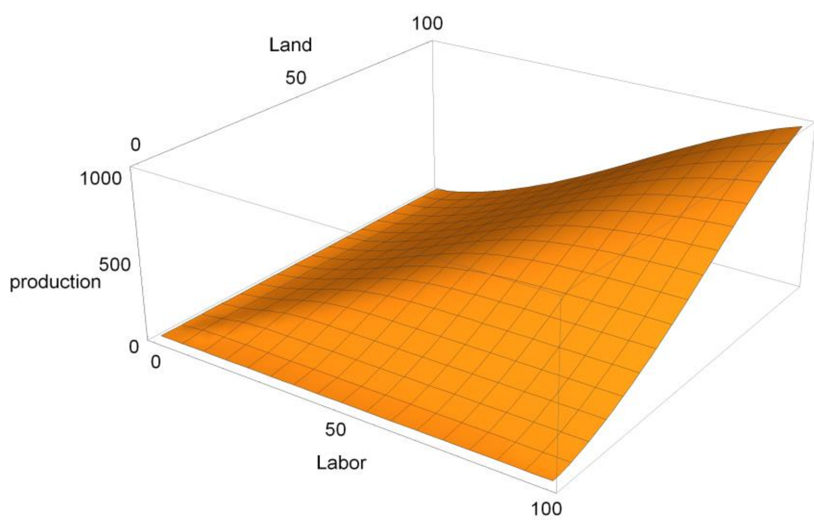


Figure 2.6. q_{LK} as a function of K for a given L.

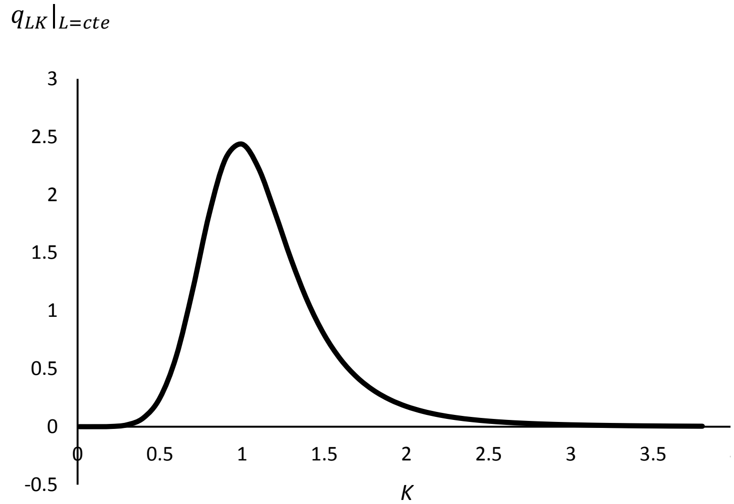


Figure 2.7. Marginal productivity of labor and mean of marginal value of education

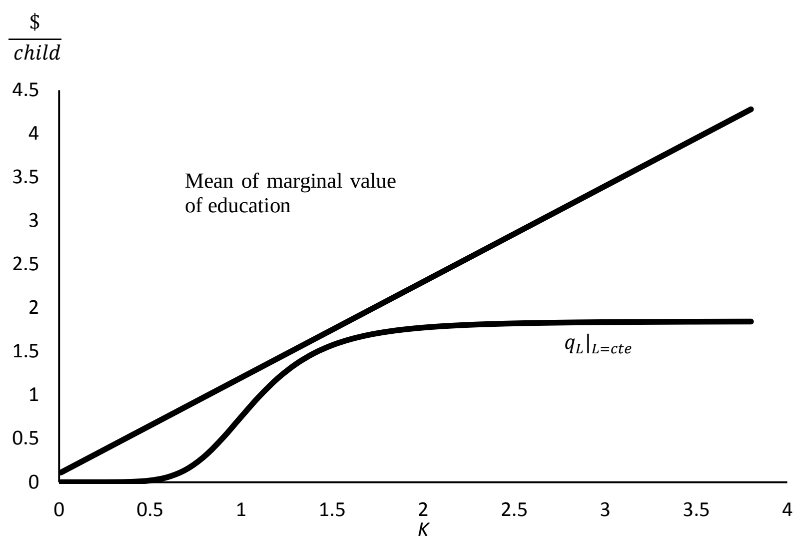
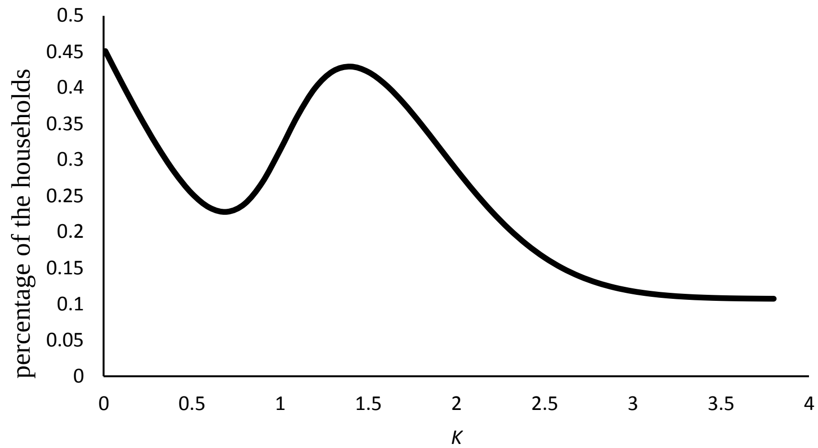


Figure 2.8. Percentage of the households who send their children to work versus land holding.



2.3. Empirical Analysis

2.3.1. 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) 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. These surveys use similar sampling designs and questionnaires and are representative at the provincial level. Our analysis focuses on households in rural areas.

2.3.2. Variables

Child labor (the dependent variable) is defined based on school attendance of children aged 7-14 in rural areas. If a child is not in school[4] and the absence is not because of illness, then he/she is considered to be a child laborer, so child labor is represented as a dummy variable equal to 1 if the child is not in school and is equal to 0 otherwise. To the best of our knowledge, those papers that use this definition do not consider the issue of the illness of a child. If a child does not attend in school, while the absence is because of illness, then it is hard to consider him/her as a child laborer. However, there are not many children who have left school due to illness. There are only 49 children aged 7-14 across all three surveys. This definition has some limitations. First, it is possible that a child does not go to school and also does not work, but its probability is very low that a child who is dropped out of school stays in home and does not work in rural areas of non-developed countries (especially in SSA). Second, in developed countries, if a child is in school and also works more than a specific amount of time, he/she may be considered as a child laborer. But, in developing countries (especially in SSA) we compromise and do not consider the children that go to school and work as a child laborer. This definition of child labor is widely used in previous researches (see, for example, Bhalotra and Heady 2003).

As we saw in the theoretical section, the household labor pool is fixed while the amount of land owned by the household varies. Since households use different amounts of labor, we divide landholding by the total number of household members more than 6 years old[5] (L) and in this

[4] There is a question in the questionnaire which asks: Has (name) ever attended school? and its answers are: 1) never been; 2) at school; and 3) left school. School attendance is defined based on this question. If the child is at school then he/she is not considered as a child laborer.

[5] We explain by an example why land size is divided by the number of individuals in household more than 6 years old. Suppose two households (A and B) both have 1 hectare, 3 adults, and 1 child whose age is between 7 and 14. Suppose the child of family A works and that of household 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

way our main independent variables $\frac{K}{L}$, $(\frac{K}{L})^2$ and $(\frac{K}{L})^3$ are constructed. Other variables are listed in Table 2.1 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 very small, reflecting less than 2 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.

We use land owned since it is typically considered exogenous to the child labor decision (see, for example, Bhalotra and Heady (2003); Lima et al (2015)). Because, land is usually inherited and land markets are undeveloped, particularly in countries like Zimbabwe, where customary tenure predominates. The buying and selling of land is limited by a weak land market in developing countries (see, for example, Swain 2001, Rosenzweig and Wolpin 1985). We examined the surveys and found that there is approximately no agricultural land market in Zimbabwe. Because, there were only 4, 2 and 24 households respectively in 2001, 2007 and 2011 that had sold or bought agricultural land in both urban and rural areas.

In addition to the above discussions, there is also another reason for the exogeneity of land owned specifically in Zimbabwe. It was explained that in 1979, only 5% of the population of

is associated with a higher probability of having a working child, in other words, $\frac{K}{L}$ is correlated negatively with the probability of being a child laborer. For solving this problem, you may want to divide land by 4 (household size), but there will still be another problem. Suppose family B has a child who is less than 7 years. 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, so they need to the same amount of workers, but A child who is less than 7 is too small to work in the field and must not be reflected in our independent variable. Therefore, we divide land (K) by the total number of individuals in each household who are more than 6 years old (L).

Zimbabwe were white, while they owned 70% of the most fertile land. But, Land reform began in 1980 by Lancaster House Agreement. And after that there were several other land reforms. As a result of the land redistributions, our surveyed data sets show that respectively in 2001, 2007 and 2011, 84%, 86% and 87% of rural households owned a piece of land. Most of these people are black Zimbabweans since most the white people left the country during the process of land reform. As we see most of people have obtained a piece of land either by inheritance or land reform, and also there is no land market in Zimbabwe for selling/buying land, therefore land owned is exogenous in Zimbabwe[6].

For calculating an asset index in rural areas separately in each year, we have used multiple correspondence analysis based on the ownership of some assets (Oryoie, Tideman and Alwang 2016). The assets are: 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, fridge freezer, bicycle, television, radio, telephone and sewing machine.

---

[6] It might be thought that land invasions in 2000 may pollute exogeneity of land owned, but the amount of occupied lands was very small. Most of the invasions were done 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), and Provinces 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 3 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 , and also there were some other land reforms after that as well (Mabaye 2005; Moyo 2011; Marongwe, 2002).

Table 2.1. Definition of variables and descriptive statistics.

Variable	2001	2007	2011	Definition
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 6 years old.
Assets	0.40 (0.21)	0.26 (0.28)	0.39 (0.26)	Asset Index.
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 1 if a child is male, and 0 otherwise.
Head male	0.60 (0.49)	0.63 (0.48)	0.64 (0.48)	Equal to 1 if head is male and 0 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 1 if head has received at least a primary school certificate and zero otherwise.
Sibling	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 less than 7	0.64 (0.81)	0.61 (0.80)	0.63 (0.79)	Number of males in household 6 years old and younger
Females less than 7	0.64 (0.81)	0.60 (0.77)	0.63 (0.78)	Number of females in household 6 years old and younger.
Males 15-50	1.13 (0.96)	1.22 (1.03)	1.14 (0.95)	Number of males between 15 and 50 years old
Females 15-50	1.38 (0.92)	1.40 (0.95)	1.26 (0.86)	Number of females between 15 and 50 years old
Males above 50	0.28 (0.46)	0.30 (0.48)	0.29 (0.46)	Number of males above 50 years old
Females above 50	0.32 (0.50)	0.36 (0.52)	0.37 (0.52)	Number of females above 50 years old
primary school	3.14 (10.7)	3.54 (16.25)	3.36 (21.30)	Distance to Primary school in Km.
Secondary school	6.81 (6.03)	6.12 (14.91)	5.94 (16.92)	Distance to Primary school in Km.

2.3.3. Estimated equation

The vector of characteristics of the ith child is denoted by X_i and that of the 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. The dependent variable y_{ihj} is a dummy variable equal to 1 if the ith child in the hth household resident 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:

$$\begin{aligned} Pr(y_{ihj} = 1|X) &= \Pr(U_w - U_s > 0\ |X) \\ &= F(\alpha + X_i\beta_1 + X_h\beta_2 + D_j\beta_3 + \epsilon_{ihj}) \end{aligned} \tag{2.16}$$

Where $F(z) = e^z/(1+e^z)$ for a logit model (for more information about logit models see appendix C). Our logit model is separately estimated in three different years of 2001, 2007 and 2011, and errors are clustered at the household level. Consider this limitation that household is nested in ward, ward is nested in district, and district is nested in province. We clustered errors at the level of district as well, and got similar results, but we prefer to cluster at the level of household since agro-ecological conditions change considerably in different areas of the Zimbabwe.

In this equation there are 18 covariates including the cubic relation plus the regional dummies. For the purpose of parsimonious we do not control for more variables.

Our Key variables are $\frac{K}{L}$, $(\frac{K}{L})^2$ and $(\frac{K}{L})^3$, which are inside of X_h. After running regressions, we must examine the graph of the probability of a working child versus land size per worker in order to make sure that the Figure 2.3 is supported empirically.

2.3.4. Results

Estimation results of the regression of child labor on $\frac{\mathrm{K}}{\mathrm{L}}$, $\left(\frac{\mathrm{K}}{\mathrm{L}}\right)^2$ and $\left(\frac{\mathrm{K}}{\mathrm{L}}\right)^3$ are reported in Table 2.2. Under the first three columns, we see odds ratios and under the last three columns we see marginal effects at the means. Standard errors are clustered at the household level. District fixed effects are controlled. The coefficients of the first three columns are in odds units.

Table 2.2 shows that the coefficients of $\frac{K}{L}$ and $(\frac{K}{L})^3$ are less than one and $(\frac{K}{L})^2$ is more than one, and all are highly significant in all years, and Table 2.3 shows that joint insignificance of the coefficients of $\frac{K}{L}$, $(\frac{K}{L})^2$ and $(\frac{K}{L})^3$ is rejected at the level of %1 in all years, providing empirical support for the theory.

The predicted values of the probability of being a working child as a function of $\frac{K}{L}$, with their 95% confidence intervals, are shown in Figure 2.9. To find Figure 2.9, we use the estimated coefficients of the equation (2.16), and all variables are set equal to their means except per capita land holding, which varies from zero to its maximum.

Figure 2.9 shows the probability of being a child laborer (black lines) as a function of $\frac{Land}{L}$ and also percent of households with a given land holding (blue lines) as a function of $\frac{Land}{L}$. As can be seen, the bumps begin to rise at 0.6, 0.9 and 0.7 hectares per household member in 2001, 2007 and 2011 respectively, and they peak at 1.2, 2.5 and 2.5 hectares per household member respectively.

Figure 2.9 shows that when land holding is in an intermediate range, the probability of having children work on the farm is around 6.5%, 11% and 6% respectively in 2001, 2007 and 2011, so the probability of sending to work for the children whose households have medium land holdings increased during the shock and then decreased to its previous value. But when land holding is zero, the probability falls progressively over time (11%, 11% and 5% respectively in 2001, 2007 and 2011), so that the probability is approximately equal between two cases of holding no land and holding a medium land in 2007, and even in 2011 the households who do not hold any land are less likely to send their children to work than the households who hold a medium land.

Therefore, both very 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 presumed to have an inverted U shape, and the middle group would be excluded if poverty were thought to be the sole cause of child labor. Furthermore, we see in the empirical results that it is possible for the households who do not hold any land be either less or more likely to send their children to work than the households whose land holding is in an intermediate range. Therefore, policy makers should note that 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.

In 2001, 2007 and 2011, respectively, about 11, 13 and 11 percent of households do not hold any land and 60, 68 and 67 percent of households lie in the initial diminishing part of the child labor curve and 26, 14 and 21 percent of households lie inside of the bump and 3, 5 and 1 21 percent of households lie in the second diminishing part. In 2001, 2007 and 2011, respectively, 2, 1 and 1 percent of households own more than 3, 4.5 and 4.5 hectare per capita.

With respect to the asset index, the odds ratios are less than one and significant for all years, and the marginal effects are all negative and significant for all years. Therefore, the probability of having a child laborer decreases as unproductive wealth increases in all years included the shock.

The marginal effects of unproductive wealth (asset index) decreased over time. They were equal to -5%, -4% and -2% respectively in 2001, 2007 and 2011. We see the same pattern of changes for productive wealth as well. The marginal effects of landholding show that the probability of being a child laborer decreased by 10%, 6% and 2% for each additional owned hectare in 2001, 2007 and 2011 respectively. The explanations of why the effect of wealth on household's decision about putting their children to work or school decreased over time are left for future research.

With respect to the number of children below 7 years old, the results suggest that the more the number of children below seven, the more workload on children 7-14 years old. It means that children 7-14 years old take care of their little brothers and sisters. But, the relevant coefficients are not always significant. But, the odds ratios and marginal effects are not much significant.

About the number of adults above 15 years old in rural households, the results suggest that the more the number of adults, the less workload on children 7-14 years old. It means that adults take care of their little household members. With respect to the number of individuals above 50, all odds ratios and MEs are insignificant.

With respect to head gender, all odds ratios and marginal effects are significant. Respectively in 2001, 2007 and 2011, the odds ratios are equal to 1.1, 1.4 and 1.3, and the marginal effects are equal to 1%, 3% and 1% respectively. The results suggest that male heads are more likely than female heads to put their children to work by about 1% in normal conditions and by 3% during crisis.

With respect to the head's education, all odds ratios and marginal effects are significant. Respectively in 2001, 2007 and 2011, the odds ratios are equal to 0.7, 0.4 and 0.6, and the marginal effects are equal to -1.5%, -6.4% and -2.5% respectively. Here, the omitted class is those with education levels lower than primary certificate (illiterate or some years of primary school), so the coefficients are compared to pre-primary certificate. Therefore, when the head of a family receives at least a primary school certificate, the ratio of the probability of being child laborer to that of being student decreases, and this decrease is much larger in crisis than in normal conditions. The marginal effects show that higher education of the head is associated with a lower probability of sending children to work, and the effect of the education is about 2-4 times more during the crisis.

With respect to head's age, Odds ratios and MEs on the age of the head are all insignificant, which means that the age of the head does not affect his or her decision about putting children to work, even when they become elderly and even in the crisis.

The odds ratios and marginal effects on access to services are significant for all years. The magnitude of the odds ratios and the marginal effects are approximately the same over time. The odds ratios are about 0.9 and the marginal effects are about -0.4%. The results suggest that if a child is located in a place where infrastructure is better, it is less likely that the child is removed from school and put to work. This finding is consistent with lower travel and time costs of schooling in such areas, because schools and bus stops are closer. But the MEs are very small, may be because infrastructures are not well developed.

With respect to child's age, all odds ratios and marginal effects are significant. Respectively in 2001, 2007 and 2011, the odds ratios are equal to 1.1, 1.1 and 1.3, and the marginal effects are all equal to +1%. That is, as a child ages, the probability of being put to work increases. This finding is consistent with the idea that once a child leaves school, he or she does not return, in other words, dropping out of school is cumulative over time. The marginal effect of age is approximately constant for the three survey periods, which means that the age profile of child labor did not change over time.

With respect to child's gender, the odds ratio and marginal effect of gender is not significant in 2001, but both odds ratios and marginal effects are significant in 2007 and 2011. Respectively in 2007 and 2011, the odds ratios are equal to 1.4 and 1.3, and the marginal effects are equal to 2.8% and 1.1% respectively. The results show that male children are more probable to be put to work than female children, and this probability is higher during crisis.

We saw a similar pattern about the relation between child labor and per capita land holding across three different surveys. Therefore, our results are robust. We can also pool all years to see whether we can again observe the same pattern or not.

Another thing that we can study is the type of land. Those factors that affect the productivity of land, can affect the probability of putting children to work as well. Because, they can affect the productivity of labor. That is, the marginal productivity of labor can be changed, when the productivity of land is changed. The productivity of land changes by soil quality, rainfall, weather, etc.

Table 2.2. Odd ratios and marginal effects from the regression of child labor on land/L using a logit model, Multiple years.

	Odds			MEs		
	2001	2007	2011	2001	2007	2011
Land Holding						
$\frac{Land}{L}$	0.034***	0.277***	0.349***	-0.085***	-0.056***	-0.019***
	(-4.65)	(-3.25)	(-3.06)	(-4.57)	(-3.38)	(-2.64)
$(\frac{Land}{L})^2$	66.692***	2.275**	2.468***			
	(3.53)	(2.51)	(2.77)			
$(\frac{Land}{L})^3$	0.225***	0.866**	0.834**			
	(-2.79)	(-2.14)	(-2.40)			
Child Characteristics						
age	1.122***	1.116***	1.292***	0.007***	0.009***	0.011***
	(5.51)	(5.07)	(10.47)	(5.50)	(5.09)	(10.99)
Male	1.026	1.436***	1.294***	0.002	0.029***	0.011***
	(0.32)	(4.49)	(3.26)	(0.32)	(4.53)	(3.28)
Household Characteristic						
Head male	1.011	1.227	1.174	0.001	0.016*	0.007
	(0.09)	(1.63)	(1.45)	(0.09)	(1.65)	(1.46)
Head education	0.747**	0.396***	0.571***	-0.017**	-0.065***	-0.024***
	(-1.98)	(-7.45)	(-5.81)	(-2.15)	(-8.40)	(-6.00)
Head age	1.000	0.998	1.003	-0.000	-0.000	0.000
	(-0.03)	(-0.49)	(0.59)	(-0.03)	(-0.49)	(0.59)
Sibling	0.596***	0.453***	0.467***	-0.032***	-0.064***	-0.034***
	(-5.54)	(-7.62)	(-6.63)	(-5.57)	(-7.34)	(-6.34)
Males less than 7	1.112**	0.934	1.057	0.007**	-0.005	0.002
	(2.02)	(-1.11)	(0.97)	(2.01)	(-1.11)	(0.98)
Females less than 7	1.011	1.120*	1.045	0.001	0.009*	0.002
	(0.18)	(1.95)	(0.75)	(0.18)	(1.94)	(0.75)
Males 15-50	1.120**	1.056	1.018	0.007**	0.004	0.001
	(2.06)	(1.16)	(0.29)	(2.06)	(1.16)	(0.29)
Females 15-50	0.974	1.003	1.074	-0.002	0.000	0.003
	(-0.47)	(0.05)	(1.30)	(-0.47)	(0.05)	(1.29)
Males above 50	1.301*	1.056	1.157	0.016*	0.004	0.007
	(1.93)	(0.39)	(1.13)	(1.92)	(0.38)	(1.13)
Females above 50	0.942	0.925	0.921	-0.004	-0.006	-0.004
	(-0.55)	(-0.70)	(-0.76)	(-0.55)	(-0.70)	(-0.76)
Asset	0.470**	0.636**	0.568***	-0.047**	-0.037**	-0.025***
	(-2.57)	(-2.36)	(-3.75)	(-2.57)	(-2.37)	(-3.70)
primary school	1.003	0.999	1.002*	0.000	-0.000	0.000*
	(1.46)	(-0.56)	(1.69)	(1.46)	(-0.56)	(1.69)
Secondary School	1.014**	1.002	0.999	0.001**	0.000	-0.000
	(2.03)	(0.91)	(-0.64)	(2.03)	(0.91)	(-0.64)
Constant	0.016***	0.046***	0.002***			
	(-7.81)	(-7.38)	(-15.07)			
Observations	14098	12168	25391			
R^2	0.1	0.1	0.1			

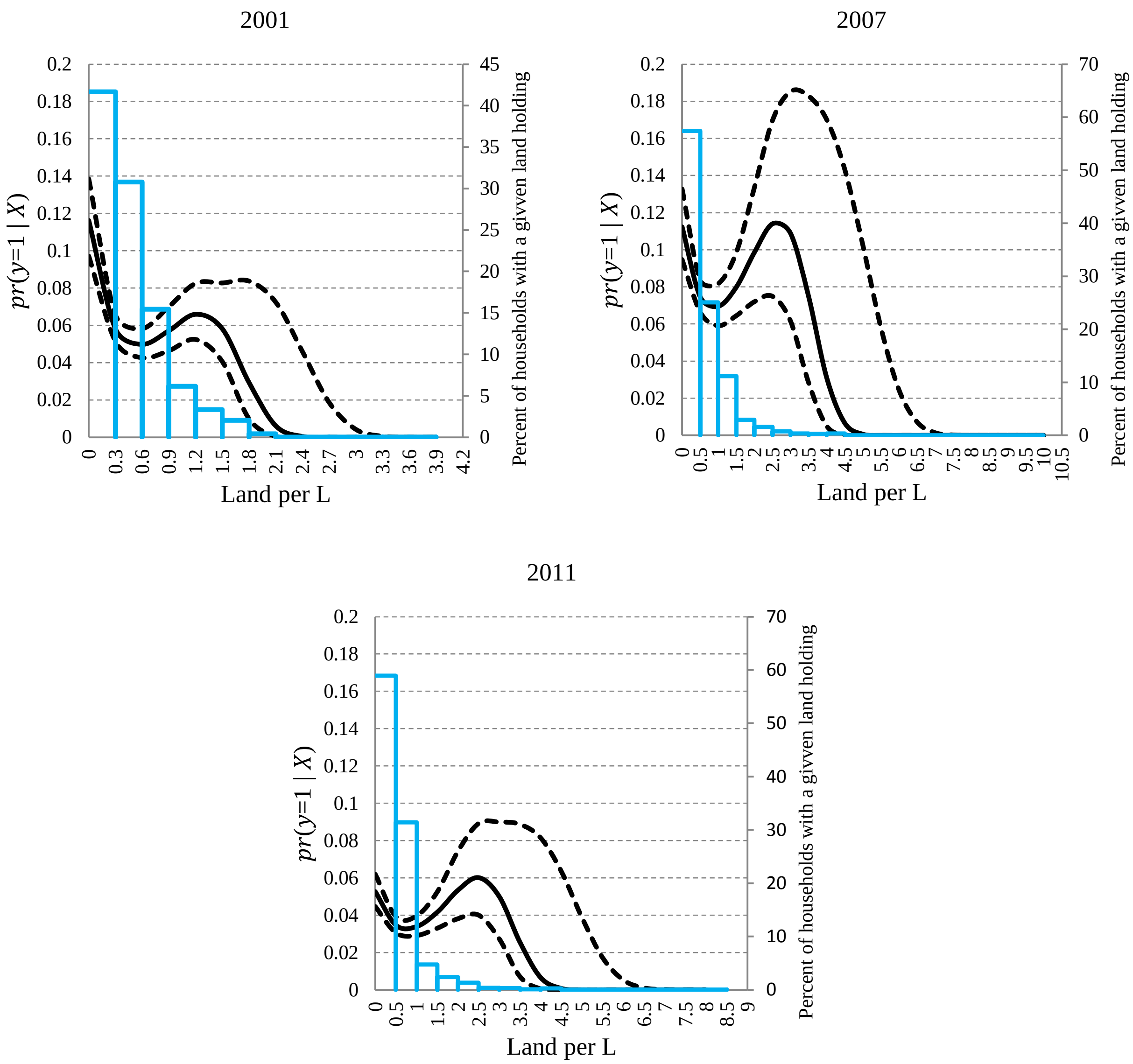
*Denotes significance at 10%, **at 5% and ***at 1%. Numbers in parentheses are t statistics. Standard errors are clustered at the household level. District fixed effects are controlled.

Table 2.3. Test of joint insignificance of land coefficients

	Chi Squared	P-value
2001	32.6	0.00
2007	14.8	0.00
2011	12.6	0.00

The Null hypothesis is that the coefficients of the cubic relation of per capita landholding are jointly insignificant

Figure 2.9. Probability of being a child labor (black lines) and percent of households (blue lines) vs. $\frac{Land}{L}$ separately in each year.



To see how the probability of putting children to work may change with changes in the productivity of land, we split the country into two parts of wet and dry. 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 can be considered as dry areas (in which rainfall is maximum 800 mm/year).

We pool all data and run a regression, and then the pooled data set is split into dry and wet areas based on the above definition, and two other regressions are run. Results are reported in table 2.4. In the first three columns we see odds ratios, and in the last three columns we see MEs. We only report the coefficients of land and asset index for the purpose of comparison of productive and unproductive wealth. All regressions include age and gender of child, age, gender and education of head, the number of siblings in school, the number of males and females below 7 years old in household, the number of males and females between 15-50 in household, the number of males and females above 50 in household, asset index, distance to primary school and secondary school and two dummies for years 2007 and 2011. Standard errors are clustered at the household level, and district fixed effects are controlled.

As can be seen, all odds ratios are again significant. By comparing the MEs of the per capita land holding (productive wealth) and the asset index (unproductive wealth) in table 2.4, we find 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 in wet and dry areas. In wet areas, the probability of being a child laborer falls by 6.8% for each extra per capita hectare, while the probability decreases only by 1.7% in dry areas. The larger effect in wet areas can be because of larger income effect of wet lands. Since productivity is higher on wet farms, farmers can earn more income for each additional per capita land holding in wet areas than in dry areas.

Therefore, child labor decreases more for each additional per capita land holding in wet areas than in dry areas.

Table 2.4. Odd ratios and marginal effects from the regression of child labor on land/L using a logit model, All years are pooled, Different agro ecological regions.

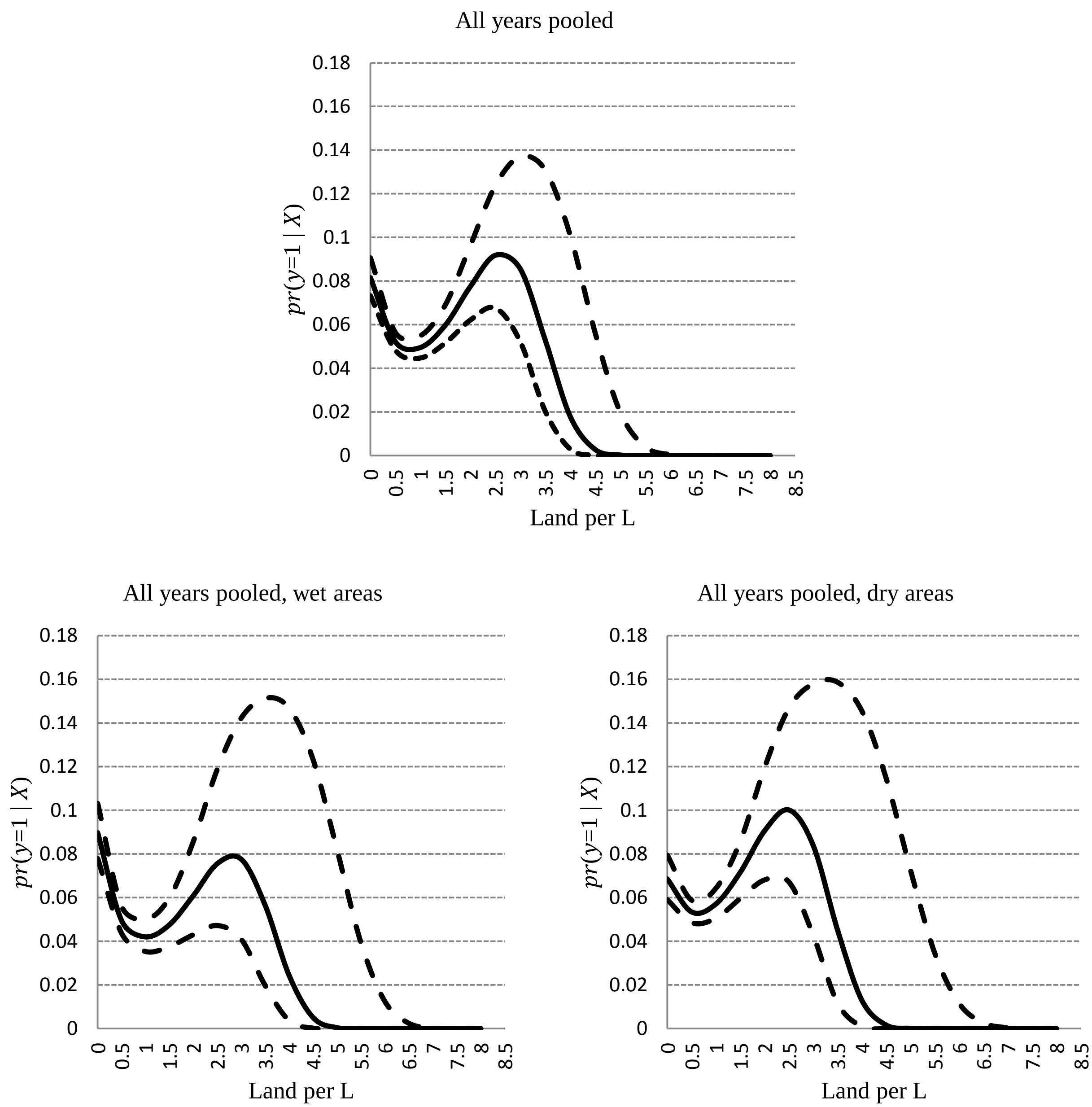
	Odds			**MEs**		
	All	**wet**	**dry**	**All**	**wet**	**dry**
Asset	0.591***	0.564***	0.600***	-0.033***	-0.036***	-0.033***
	(-4.46)	(-3.75)	(-2.76)	(-4.47)	(-3.76)	(-2.76)
$\frac{Land}{L}$	0.248***	0.164***	0.407***	-0.044***	-0.068***	-0.017*
	(-5.77)	(-5.28)	(-2.70)	(-5.56)	(-5.33)	(-1.94)
$(\frac{Land}{L})^2$	2.843***	3.245***	2.379***			
	(4.78)	(3.93)	(2.77)			
$(\frac{Land}{L})^3$	0.820***	0.814***	0.829**			
	(-3.98)	(-3.20)	(-2.52)			
Observations	51657	23697	27960			
R^2	0.08	0.08	0.08			
P-value for Test of joint insignificance of land coefficients	0.00	0.04	0.00			

*Denotes significance at 10%, **at 5% and ***at 1%. Numbers in parentheses are t statistics. Standard errors are clustered at the household level. District fixed effects are controlled. All regressions include age and gender of child, age, gender and education of head, the number of siblings in school, the number of males and females below 7 years old in household, the number of males and females between 15-50 in household, the number of males and females above 50 in household, asset index, distance to primary school and secondary school and two dummies for years 2007 and 2011. Natural regions III, IV and V are considered as dry areas (in which rainfall is maximum 800 mm/year).

We use the estimated coefficients of the equation (2.16) to draw the probability of putting children to work versus per capita land holding. We set all variables equal to their mean except per capita land, which varies from zero to its maximum. The probabilities are shown in Figure 2.10.First, as can be seen, we got the same pattern as Figure 2.9, that is, our results are pretty robust.

By comparing those households that own a very small land and those with a medium-sized holding in wet and dry areas, we find that those who own a very small land are more likely to put their children to work in wet areas than in dry areas by about 2%. And those with medium-sized land are less likely to put their children to work in wet areas than in dry areas by about 2%. That is probably because the productivity of arable farms is higher than dry farms, so incentive for putting children to work for very poor households is higher in wet areas than in dry areas. But, the probability is lower for the households with medium land holdings in wet areas because they are rich enough in wet areas.

Figure 2.10. Probability of being a child labor vs. $\frac{Land}{L}$ when all years are pooled.



2.4. Conclusion

Many studies have shown that an important determinant of child labor is wealth. 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.

We show that the likelihood that a household puts its children to work generally falls as productive wealth (land) increases, 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.

We discuss that in wet areas the productivity of land is higher, and this higher productivity from one side causes more incentive for putting children to work for very poor households in wet areas, and from another side, equal increases in wet land owned leads to sharper decline in child labor in comparison to dry land owned because of higher income effect of wet lands.

From the perspective of seeking policies to reduce child labor, the results show that programs should be designed to get farmers "over the hump," to where the marginal product of labor declines as wealth increases. For the very poor, a small amount of increased land will decrease the temptation to remove children from school. Households with medium-sized holdings, however, may be at risk of removing their children from schools. Thus programs to promote school retention should not necessarily focus only on the poorest households in rural areas.

Chapter 3

Child Labor and Hyperinflation in Zimbabwe

3.1. Introduction

Child labor is common around the world, particularly in developing countries. In 2010, sub-Saharan Africa (SSA) had the highest rates of working children, with 26.2 percent of children aged 5–14 being employed in 2012 (Diallo, et al 2013). SSA is the poorest region of the world, and it also has the youngest population (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.

The majority of working children in SSA are involved in agriculture, frequently being employed on their parents' farms (Edmonds and Pavcnik 2005). As reductions in child labor, associated with increases in investments in human capital, can improve long-run economic growth, factors associated with use of child labor in agriculture should be identified.

Zimbabwe is one of SSA countries where achievements in schooling are particularly noteworthy (Larochelle, Alwang and Taruvinga 2014). Achievements in education and 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 many ways more severe than those of a typical developing country. In the decade beginning in 2000 the economy was consumed by hyperinflation (see appendix A for the magnitude of the hyperinflation), falling incomes, and political instability. These problems led to widespread suffering and emigration of professional workers including teachers and nurses. After a long period of relative stability since Independence in 1980, inflation began to grow in 1997 due mainly to fiscal imbalances. The appearance of inflation coincided with growing impatience with the slow process of economic restructuring and the lack of opportunity. In rural areas, veterans of the independence struggle began protesting perceived inadequacies in earlier land reform efforts, and farm invasions began in the late 1990s. These invasions had the effect of pushing land reform to the front of the policy dialog, although land reform had started since 1980 by Lancaster House Agreement (Moyo 2011; Mabaye 2005).

Following a prolonged downward spiral in economic conditions, the country experienced a severe hyperinflation in 2007 and 2008 (Hanke, Kwok 2009). 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 increasing[7] (Richardson 2013).

Sending children to work instead of school implies less human capital attainment and long-term reduction in economic growth, as the human capital stock is an important determinant of national economic growth (Jacoby and Skoufias 1997; Barro 1991). Decisions about whether to send children to school or to work are affected by factors such as poverty, lack of resources, credit constraints, school quality, parental attitudes toward education, and imperfect credit and labor markets (Dumas (2015); Basu and Van (1998); Ersado 2005; Jacoby and Skoufias 1997; Weir 2011; Guarcello et al. (2002); see also Edmonds (2007) for a literature review). In addition

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

to these factors, in rural areas, Oryoie, Alwang and Tideman 2016 found that Child labor generally decreases as per capita land holding increases, but there is a persistent upward bump in the relationship between child labor and landholding near the middle of the range of land per capita. In other words, both very poor households and households with medium-sized holdings are likely to have a high incidence of child labor

In this chapter, we study the role of shocks on decisions about sending children to work. In most less developed countries, the main source of income for rural households stems from agriculture. Agriculture is also susceptible to high uncertainty. Agricultural households are exposed to negative/positive shocks such as climate problems such as drought and heat stress, good rain falls, price variability, and agricultural pests. Due to credit/insurance market failures, formal risk management is complicated. Informal risk sharing strategies and mechanisms may exist, but such mechanisms tend to be inadequate in the face of widespread covariate shocks. Absence of coping tools contributes to a large variance of income and consumption and households may respond to shocks by removing their children from school.

It is theoretically indeterminate whether investments in children increase or decrease during negative/positive shocks. Suppose there is an adverse shock (like the hyperinflation in Zimbabwe) that reduces the price of agricultural products relative to other market-purchased goods. The shock affects the decision to put children to work via substitution and income effects. The direction of impact on this decision depends on which effect dominates.

From one side, the shock causes the rural households to get poorer, so child labor increases (Income effect). In this case we would observe procyclical human capital investments. From the other side, as a result of the relative price fall, the opportunity cost of time of children and adults fall, so child labor decreases, and parents may even have more free time to take care of their children (Substitution effect). In this case we would observe countercyclical human capital investments. Thus theory cannot predict the direction of the effect of the shock on the amount of child labor. Therefore, how child labor changes after a price shock is an empirical question.

Understanding the mechanism driving household decision making about schooling and child labor during positive/negative shocks has important implications for policy makers wishing to reduce child labor. If the income effect dominates, safety net programs should be a priority during negative shocks, and if substitution effect dominates, then children are pulled out of school during positive shocks, so policy makers need be more cautious about child labor and schooling during positive shocks. Policy can lower costs of education and increase incentives for putting children in school during positive shock by providing voucher programs and subsidies to the school. For example, if a very good rain fall is forecasted in one part of a country, then we might expect an increase of child labor use, and policy makers should focus on areas where the positive shock is most prominent.

Many researchers have already studied the effects of shocks on the education/work of children. Many of these studies have been conducted using data from low income African, Asian and Latin American countries. Some studies show that investments on education are procyclical. For example, Cogneau and Jedwab (2012) studies the impact of a fall in producer price of an export crop (cocoa) on investments in children in Coˆte d'Ivoire, and they find that human capital investments are procyclical. Edmonds and Pavcnik (2005) show that Rice price increases are associated with declines in child labor in Vietnam. Beegle et al. (2008) show that crop shocks (pests or fire) or rainfall shocks lead to an increase in child labor in Tanzania (for more examples see Thomas et al. (2004) for Indonesia; Duryea et al. (2007) for Brazil; Jensen (2000) for Coˆte d'Ivoire). Some studies show that investments on education are countercyclical. For example, schady (2004) studies the effects of a deep macroeconomic shock (30% decrease in GDP) in Peru on school attendance and employment of children. The did not find any evidence that school attendance decreased during the crisis, and they showed that children exposed to crisis were less likely to work and completed more grades than children unexposed to the crisis. In addition, some papers show that the decision making mechanism can be different for different groups of a society. For, example Kruger (2007) shows that during positive shocks in Brazil, education of poor children may be affected negatively, but education of rich children may not. Thomas et al. (2004) find similar results for Indonesia. Dumas (2015) shows that child labor increases when there is a positive shock in rainfall in Tanzania, but the amount of increase is less for the households who have access to labor markets (see also Jie Bai (2015)).

SSA countries appear to be different from other low income countries, because children in SSA suffer from malnutrition and mortality more than other low income countries. Children might be in very dangerous situation during negative shocks due to the malnutrition, and consequently, they work more during the negative shocks for surviving. That is, it is expected that income effect dominates in SSA. In this chapter, we study Zimbabwe, and it will be shown that educational investments are countercyclical. That is, opposite of expectation, substitution effect dominates and policy makers wishing to reduce child labor should be more concerned during positive shocks. Furthermore, we run two separate regressions for wealthy and poor households to explore the differences in the mechanism of the decision making of poor and wealthy households. We find that the substitution effect dominates for both groups during the crisis.

Our data set comes 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.

The remainder of the chapter is organized as follows: empirical specification is presented in section 3.2. A description of the data and variables is presented in section 3.3. The results from the empirical estimations are found in Section 3.4, and we conclude in Section 3.5.

3.2. Empirical specification

Harvest time[8] is our main independent variable, used to identify the effects of the shock on the education decision. When prices increase sharply every week (see Appendix A), all prices change in an unpredictable fashion, and it is not clear which product prices increase more rapidly and which ones less. Farmers are unaware of prices after harvest, and they do not know whether the real price of their product will be higher or lower than past times. It is generally the case that the price of agricultural products falls after harvest due to rise of supply, but when there is hyperinflation, it is not predictable how much the prices will fall nor how they will change

[8] Harvest time in Zimbabwe depends on the pattern of movement of weather and type of agricultural products. weather travels from west to east, so harvest time of similar products is sooner in west, and some of the agricultural products are harvested sooner than others. Furthermore, some products are harvested only in west and some only in east because of differences in agro ecological characteristics. Because of these complications we cannot determine a specific month as harvest time in Zimbabwe, but most of main products are harvested from May to June. Remember that we have dropped months January-May, therefore only June is considered as harvest time. But, we consider July as harvest time as well. Because, first, due to weather changes harvest can be postponed in one year, second, it takes some time until farmers sell their products and realize their real income, so it takes some time until they make their decision about children. That is, we cannot see their behavior immediately at the end of June, therefore July is considered as harvest time as well.

relative to other prices. Farmers observe the price of their products only after harvest, and when they go to market they become aware of the degree to which the hyperinflation affects them. By studying behavior before and after harvest time across different years, evidence is obtained on how decision making occurs. We do not claim that they have no sense about the prices before harvest. The process of gaining information about the price is gradual and sequential, but they will know the real prices after harvest with much more certainty.

Consider that the structure of survey is approximately balanced between two times of harvest and after that. We have approximately equal number of observations each month, and the mean values of main demographic and location variables approximately do not vary before and after harvest.

Before analyzing income/substitution effects, we need to see whether the households experienced a negative shock or a positive shock in 2007. We exploit the timing of the PICES surveys to examine differences in behavior of agricultural households before and after the period of harvest. It is generally expected that hyperinflation is considered as an adverse shock. In rural areas of Zimbabwe most households state that their main source of income comes from sale of own agricultural products or their main activity has been farming during the past twelve months (78, 89 and 85 percent respectively in 2001, 2007 and 2011). Therefore, we treat all rural households as farm-households. We can split farmers into two groups of net sellers and net buyers of agricultural products. Hyperinflation affects negatively net buyers, so the shock is a negative shock for them. But, if agricultural product prices were rising more rapidly than non-agricultural prices, then it might be thought that the net sellers of agricultural products saw their wealth increase due to hyperinflation and the shock was a positive shock for them.

In order to establish whether net sellers were affected negatively during the hyperinflationary period, we calculate inflation for main crops of Zimbabwe between years 2006 and 2007 using a producer price index (PPI), and compare these estimates to estimated inflation for consumption expenditures using CPI for the same years. We will see that the CPI increased much more sharply than the PPI, signaling that net sellers got poorer as relative prices changed. To confirm this negative shock to income/wealth, we calculate an asset index using multiple correspondence analysis (MCA) on assets owned by the rural households in each year (Oryoie, Tideman and Alwang (2016)). Using a t-test for equality of mean of asset index, it will be shown that rural households sampled before the harvest period had fewer assets than those sampled after the harvest in normal conditions (2001 and 2011). In contrast, in 2007, post-harvest asset indices are lower than they were prior to the harvest, an additional indication that the hyperinflation was associated with declining wealth in rural Zimbabwe. These results are consistent with the changes of the price indices explained in the beginning of this paragraph. Therefore, there is no doubt that the shock affected all of the rural households adversely included the net producers.

It was explained that the shock affected farmers negatively. This shock can be considered as a large decrease in the relative price of agricultural products. After harvest, farmers see that their income falls. This income effect should be expected to lead to a rise in child labor. At the same time opportunity cost of time of children falls (demand for child labor falls) due to the decrease in the relative price of agricultural output. This substitution effect causes a decrease in child labor. In order to see which effect dominates, we regress child labor on a dummy for harvest time and a complete set of covariates in each year. We find convincing evidence of an increase in child labor following harvest in 2001 and 2011, but a decrease after harvest in 2007 during the economic crisis. Results show that the substitution effect dominates the income effect in Zimbabwe.

3.3. Data description

Three nationally representative household surveys conducted by ZIMSTAT are employed for the analysis. The Incomes, Consumption and Expenditure Surveys (ICES) were conducted from the first of January 2001 to the 10^{th} of 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 only a few observations were collected in 2008. The Poverty, Incomes, Consumption and Expenditure Survey (PICES), which is essentially the same survey, 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. These surveys use similar sampling designs and questionnaires and are representative at the provincial level. Our analysis focuses on households in rural areas[9]. These surveys contain information on household demographics, schooling, healthcare, employment and household enterprises, asset ownership, consumption expenditures and income.

Child labor (the dependent variable) is defined based on school attendance of children aged 7-14 in rural areas. If a child is not in school[10] and the absence is not because of illness, then

[9] Consider that the 2007/8 ICES survey was not conducted from January of 2008, and also the data collection of the 2001 ICES survey began in January, while the data collection of other years was started from June. Because time order is important in our analysis, we have to drop the observations which are collected from January to May in 2001 and 2011 in order to be able to compare the behavior of the farmers after harvest across different years during the same period of time.

[10] There is a question in the questionnaire which asks: Has (name) ever attended school? and its answers are: 1) never been; 2) at school; and 3) left school. School attendance is defined based on this question. If the child is at school then he/she is not considered as a child laborer.

he/she is considered to be a child laborer, so child labor is represented as a dummy variable equal to 1 if the child is not in school and is equal to 0 otherwise. To the best of our knowledge, those papers that use this definition do not consider the issue of the illness of a child. If a child does not attend in school, while the absence is because of illness, then it is hard to consider him/her as a child laborer. However, there are not many children who have left school due to illness. There are only 49 children aged 7-14 across all three surveys. This definition has some limitations. First, it is possible that a child does not go to school and also does not work, but its probability is very low that a child who is dropped out of school stays in home and does not work in rural areas of non-developed countries (especially in SSA). Second, in developed countries, if a child is in school and also works more than a specific amount of time, he/she may be easily considered as a child laborer. But, in developing countries (especially in SSA) we compromise and do not consider the children that go to school and work as a child laborer. This definition of child labor is widely used in previous researches (see, for example, Bhalotra and Heady 2003).

Independent variables are listed in Table 3.1 with their definitions and summary statistics. It is necessary to explain a little bit about per capita land holding (Land per L) and asset index. Oryoie, Alwang and Tideman (2016) show theoretically and empirically (for rural Zimbabwe) that there is a nonlinear cubic relation between child labor and per capita land holding.

An asset index is calculated for each household using multiple correspondence analysis based on common assets owned by households (Oryoie, Tideman and Alwang 2016). The assets are chosen such that they can be sold/bought easily in short run, because we want to see whether the households sell or buy their assets before and after harvest. The assets we use are: plough, wheelbarrow, scotch cart, tractor, grinding mill, videotape/DVD, juice extractor, toaster, food mixer, washing machine, electric heater, stove, motor vehicle, fridge freezer, bicycle, television, radio, telephone, sewing machine.

Table 3.1. Definition of variables and descriptive statistics

Variable	Mean (sd) 2001	2007	2011	Definition
Dependent Variable	0.07 (0.26)	0.10 (0.29)	0.06 (0.23)	A dummy variable equal to 1 if a child aged 7-14 is not in school while his/her not-attendance is not due to illness, and zero otherwise.
Age	22.30 (19.06)	22.85 (19.47)	22.69 (19.90)	Age of child.
Male	0.48 (0.50)	0.48 (0.50)	0.48 (0.50)	a dummy variable equal to 1 if a child is male, and 0 otherwise.
Head education	0.26 (0.44)	0.34 (0.47)	0.45 (0.50)	A dummy variable equal to 1 if head has at least a primary certificate and zero otherwise.
Head gender	0.64 (0.48)	0.65 (0.48)	0.65 (0.48)	Equal to 1 if head is male and 0 otherwise.
Head age	46.92 (15.28)	47.76 (16.35)	47.86 (16.36)	Age of head of household.
Males less than 7	0.64 (0.81)	0.61 (0.80)	0.64 (0.79)	Number of males in household 6 years old and younger.
Females less than 7	0.64 (0.80)	0.60 (0.77)	0.63 (0.78)	Number of females in household 6 years old and younger.
Males 15-50	1.15 (0.98)	1.22 (1.03)	1.14 (0.95)	Number of males in household between 15 and 50 years old.
Females 15-50	1.39 (0.94)	1.40 (0.95)	1.27 (0.86)	Number of females in household between 15 and 50 years old.
Males above 50	0.28 (0.46)	0.30 (0.48)	0.28 (0.46)	Number of males in household greater than 50 years old.
Females above 50	0.31 (0.50)	0.36 (0.52)	0.36 (0.52)	Number of females in household greater than 50 years old.
Land per L	0.73 (14.29)	0.65 (5.40)	0.56 (0.63)	Amount of land holding in hectares divided by the number of individuals in household greater than 6 years old.
Asset	1.86 (4.69)	1.94 (4.68)	4.08 (6.47)	Asset index[1]
School fee	0.02 (0.04)	0.03 (0.03)	0.04 (0.04)	Mean of School fee[2] divided by total consumption expenditures in each ward and each month.
primary school				Distance to Primary school in Km.
Secondary school				Distance to Primary school in Km.

1. Asset index is scaled such that it varies from 0 to 100.
2. Pre-school fees, School tuition fees (excluded payments for food, beverage & shelter), Parents and Teachers' association fee or levy or building fund, uniform, School shoes, School sports wear, Exercise books, Ball pens, pencils, erasers and other stationery for school, Educational books ,School bus or transport cost, Boarding fees, Other tuition and correspondence fees, Other expenses on education

3.4. Empirical Analysis

3.4.1. Was the hyperinflation a negative shock or a positive shock?

In this section, we will show that all rural households are affected negatively in 2007.In section 2, it was explained that all rural households are split into two groups of net sellers (producers) of agricultural products and net buyers f agricultural products. Hyperinflation affects the net consumers negatively, so the shock is a negative shock for them. But, if agricultural prices were rising more rapidly than non-agricultural prices, then it might be thought that the net producers of agricultural products got richer and the shock was a positive shock for them.

We know that all prices including those of agricultural products were increasing quickly every week in 2007 (Hanke and Kwok (2009)).The easiest way to find whether net sellers are affected negatively or positively in 2007 is to compute a monthly relative price index for agricultural products. But, only a few households in the 2007 reported how much agricultural products they have sold or consumed, while most of rural households in Zimbabwe are farmers, and the selling price that they report is noisy. Therefore, we need to find another way.

We fortunately could find some annual data for CPI and PPI in the website of food and agriculture organization of the United Nations[11] (FAO) in 2000, 2001, 2006 and 2007, but there was no data for 2010 and 2011. In Table 3.2, we have reported annual inflation for main agricultural products of Zimbabwe calculated using PPI and also inflation for consumption expenditures calculated using CPI from 2000 to 2001, and from 2006 to 2007. All numbers are the percentage of the change of the price indices.

[11] http://www.fao.org

CPI increased far more than PPI in 2007. That is, the relative price of farm output decreased dramatically and farmers were disadvantaged, in other words, farmers experienced a substantial adverse shock in 2007[12]. But, the relative price of farm output compared to other goods increased in 2001; farmers received favorable prices in 2001. This fact that the relative price increased in 2001 is very helpful since it makes us enable to compare the behavior of the rural households in two opposite situations.

Table 3.2. Annual inflation rates (%)

Agricultural products	2000-2001		2006-2007	
	PPI	CPI	PPI	CPI
Maize	160%		192%	
Millet	67%		220%	
Sorghum	67%	72%	204%	6827%
Tobacco	133%		172%	
Wheat	200%		232%	

All numbers are in percentage. CPI is calculated based on consumption prices of all goods and services included agricultural goods.

The direction of the shock can be examined in a different perspective by looking at household asset holdings. A comparison of the value of asset holdings before and after harvest for the three periods will indicate if 2007 was an abnormal year. An asset index is calculated for each household in the sample using MCA. Then, mean of the index is computed for two time periods of harvest time and after the harvest. If the mean is higher after the harvest, then it means that the farmers get richer. But if they sell their products at a price lower than the price of other products, they get poorer after the harvest, so they may sell some of their assets.

In table 3.3, we test statistically whether asset index of households increased or decreased after harvest in each year. In the table, we can see P-values of the tests. The null hypothesis is that the mean of the asset index during harvest is equal to the mean of the index after harvest

[12] Prices are measured poorly in 2007, but since the difference between the inflations in CPI and PPI is very large, we are not worried about the conclusion made about the relative price.

($\overline{\text{Asset}}|_{T=0} = \overline{\text{Asset}}|_{T=1}$). There are two one-sided alternative hypothesizes, which are H1_a: $\overline{\text{Asset}}|_{T=0} < \overline{\text{Asset}}|_{T=1}$ and H2_a: $\overline{\text{Asset}}|_{T=0} > \overline{\text{Asset}}|_{T=1}$. This test is done for all three years.

Table 3.3. P-values of tests of equality of asset index before harvest and after harvest

	H1_a	H2_a
2001	0.0000	1.0000
2007	1.0000	0.0000
2011	0.0000	1.0000

The null hypothesis is $\overline{Asset}|_{harvest} = \overline{Asset}|_{after}$ and there are two alternatives H1_a: $\overline{Asset}|_{harvest} < \overline{Asset}|_{after}$ and H2_a: $\overline{Asset}|_{harvest} > \overline{Asset}|_{after}$

As we see, all p-values are either highly significant or highly insignificant. Before and after the shock the null is rejected in favor of H1_a. Therefore we conclude that households are used to buy some assets for their home or farm after harvest in normal conditions (2001 and 2011), which is reasonable, because after harvest, they sell their agricultural products and by the earned money they can buy more assets. But, during the shock, the null is rejected in favor of H2_a, which means households sold their assets after harvest, so they were getting poorer during the crisis.

In summary, we see that in normal conditions farm households buy assets after harvest, while during the crisis, they sold their assets. This finding is consistent with the changes in relative price found in Table 3.2. Therefore, we conclude that the shock affected rural households adversely. Now we are able to interpret income and substitution effects. There is no doubt that the hyperinflation affected all rural households negatively. Therefore, the income effect should lead to an increase in child labor and substitution effect should induce a decrease in child labor.

One objection to the use of the asset index arises from the possibility that the before and after harvest samples are actually of different populations. It is possible that the data was collected in rich areas prior to harvest and after harvest in poor areas in 2007, while the process of data collection was opposite in 2001 and 2011. Such sampling patterns could be associated with the results, to check this possibility, we checked the distribution of the observations, and also we checked the balance of covariates by testing equality of the means of the covariates between harvest time and after harvest. We found that all covariates are balanced except asset index, school fee and the number of Males less than 7. The results are reported in table 3.4 It is reasonable why asset index and school fee are not balanced. We know that prices were increasing every week, so it is clear that these variables cannot be balanced.

Table 3.4. t-test for equality of mean of different variables during harvest and after that in 2007.

Variables	**P-Values**	**Variables**	**P-Values**
Head education	0.10	Age	0.74
Male	0.39	Head male	0.10
Males less than 7	0.00	Head age	0.64
Females less than 7	0.05	$\frac{Land}{\mathrm{L}}$	0.09
Males 15-50	0.43	Primary School	0.60
Females 15-50	0.91	Secondary School	0.17
Males above 50	0.29	School fee over total consumption	0.00
Females above 50	0.46	Assets	0.00

The reported numbers are P-values. The null hypothesis is that the mean of a variable during harvest is equal to its mean after the harvest.

3.4.2. Estimated equation

The vector of characteristics of the ith child is denoted by X_i and that of the household characteristics are denoted by X_h. R_j is a dummy variable for region j, which controls for regional fixed effects at three different geographical levels of province, district and sub-district[13], and T is a dummy equal to zero in harvest time and 1 after harvest. I_{jm} indicates school fee in region j and month m. Suppose X shows the vector of all independent variables. The dependent variable y_{ihjm} is a dummy variable equal to 1 if the ith child in the hth household resident in region j in month m 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 $y_{ihjm} = 1$, unless $y_{ihjm} = 0$. It can be shown that:

$$\begin{aligned}\Pr(y_{ihjm} = 1|X) &= \Pr(U_w - U_s > 0|X) \\ &= F(\alpha + X_i\beta_1 + X_h\beta_2 + R_j\beta_3 + \beta_4 I_{jm} + \beta_5 T \\ &\quad + \epsilon_{ihjm})\end{aligned} \tag{3.1}$$

Where $F(z) = e^z/(1 + e^z)$ for a logit model (for more information about logit models see appendix C). Our logit model is separately estimated in three different years of 2001, 2007 and 2011, and errors are clustered at the household level. Consider this limitation that household is nested in ward, ward is nested in district, and district is nested in province. We clustered errors at higher levels as well, and got similar results, but we prefer to cluster at the level of household since agro-ecological conditions change considerably in different areas of the Zimbabwe.

[13] After district, the smallest unit of census areas is ward. There are a few households by ward in the sample who have a child aged 7-14. The relatively small sample size by ward causes our dependent variable not to vary within in many wards. Consequently, after running regressions, all of those households who are in the wards are omitted because of collinearity. Therefore we need to merge wards such that our dependent variable varies in each ward. To this end, we have divided each district into 2 or 3 parts based on the closeness of wards to each other and these parts are called sub-district in this chapter.

It is possible that during the price shock some unobservable variables change, and that these unobservable variables are the main factors that affect child labor, not the price shock. The only thing that we can do to mitigate the problem caused by potential unobservables is to control for regional fixed effects. We control for school fee as well. School fee vary monthly in each region, so in this way we control for the changes of school fee between regions and within regions over time. To deflate school fee, we have divided it by total consumption expenditures. Inclusion of these variables allows for the possibility of unobserved institutional changes during the crisis which change the pattern of changes of child labor.

Estimation results of equation (3.1) are reported in Table 3.5. In this Table we report only the coefficients of the time dummy. Under the first three columns, we see estimated odds ratios and under the last three columns we see marginal effects (ME).

In order to make sure that our results are robust, we control for different unobserved regional fixed effects by changing the size of regions from province to sub-districts. As we move downward in the Table from model 1 to model 5, our regional controls become more geographically specific. In the first regression, there is no regional fixed effect. In the next ones we control for unobserved fixed effects at the level of province, district and sub-districts respectively, and finally in model 5 we include school fee, which changes monthly at the level of ward.

Respectively in 2001, 2007 and 2011, there are on average 192, 283, and 382 rural households in the sample who have a child aged 7-14 in each province, and there are on average 28, 39 and 52 households in each district, and finally there are on average 16, 23 and 31 households in each sub-district[14]. Because there are only a few households in each sub-district, by controlling for unobserved sub-district fixed effects, we are minimizing biases caused by unobserved household fixed effects (the best we can do in the absence of panel data).

As we see in Table 3.5, odd ratios and MEs of time dummy are significant and pretty stable in all years and all regressions. The interesting finding is about the magnitude of the odd ratios and the sign of MEs of time. Let's consider only the results of the model 5 in which there are more covariates and the regional fixed effect is the smallest one, although both odds ratios and MEs or approximately identical across all models. The MEs show that child labor increases after harvest by about 2% in 2001 and 1% in 2011, but it decreases by about 2% after harvest during the crisis. And the odds ratio is more than one after harvest in 2001 and 2011 (about 1.3 in both years), but it is less than one after harvest during the shock (about 0.8). That is, the probability of putting a child to work is more than putting to school after harvest in normal conditions, but the probability is inverse during the shock.

We see a dramatic change in the behavior of rural households during the inflationary shock. We already saw that the relative price of agricultural products decreased during the shock and rural households got poorer after harvest, but they got richer after harvest in both 2001 and 2011. Therefore, as we see, when households get richer child labor increases and when they get poorer child labor decreases. That is, the substitution effect dominates income effect in rural areas of Zimbabwe. Therefore, policy makers wishing to reduce child labor need to be more careful during positive shocks.

[14] remember that we dropped the households who were surveyed from January to May

Here, a concern may arise. One might think that timing of academic year and vacations may cause the decrease in child labor in 2007. But, consider that if this is a case, it must show up in 2001 and 2011 as well. Therefore, we should not be concerned about timing of academic year.

In all regressions of Table 3.5, we controlled for the number of Males/ Females less than 7, age of child, gender of child, age and gender and education of head, services, a cubic polynomial of per capita land holding and regional fixed effects, but model 1 in not included regional fixed effects. Furthermore, the model 5 include mean of school fee in each month and each sub-district as well. We tested the balance of covariates during and after harvest; they are all stable (balanced) during the 2007 crisis except for the wealth index, school fees and access to services. By including unbalanced variables in the regression, their effects are controlled for.

It is pretty reasonable that the mechanism of decision making be different between poor households and wealthy households. We can expect that the income that wealthy households earn after harvest does not affect them such that they change their mind about putting children in school or pulling them out of school. They are wealthy and temporary changes of income affect them less. But, the story is different for poor households. Income changes may affect them prominently. In order to see whether or not wealthy households behave differently from poor households after harvest during crisis, and also in order to check again for further robustness of results, we divide households into two categories of poor and wealthy. For the classification we use the mean of the asset index separately in each year.

Table 3.5. Odd ratios and marginal effects of time dummy on school-aged child working, various model specifications

Models	**Odds**			**ME**		
	2001	2007	2011	2001	2007	2011
No Fixed effect(1)	1.247*	0.747***	1.320**	0.015*	-0.025***	0.012**
	(1.82)	(-3.18)	(2.40)	(1.91)	(-3.07)	(2.48)
Province fixed effects(2)	1.279**	0.747***	1.333**	0.016**	-0.025***	0.012***
	(2.02)	(-3.13)	(2.52)	(2.13)	(-3.03)	(2.61)
District fixed effects(3)	1.304**	0.751***	1.288**	0.017**	-0.024***	0.011**
	(2.03)	(-3.09)	(2.26)	(2.14)	(-3.00)	(2.33)
Sub-district fixed effects(4)	1.323**	0.790**	1.272**	0.017**	-0.022***	0.009**
	(2.07)	(-2.46)	(2.04)	(2.00)	(-2.75)	(2.00)
Sub-district fixed effects included school fee over total consumption expenditures(5)	1.300*	0.754***	1.213*	0.017**	-0.023***	0.008*
	(1.93)	(-2.92)	(1.68)	(2.02)	(-2.83)	(1.72)
R^2	0.08	0.10	0.11			
Observations	8646	12184	14675			

*Denotes significance at 10%, **at 5% and ***at 1%. Numbers in parentheses are t statistics. Standard errors are clustered at the household level. Marginal Effects are calculated at means. All regressions include age and gender of child, age, gender and education of head, the number of siblings in school, the number of males and females below 7 years old in household, the number of males and females between 15-50 in household, the number of males and females above 50 in household, asset index, distance to primary school and secondary school, a cubic polynomial of per capita land holding and regional fixed effects, but model 1 in not included regional fixed effects. The model 5 include mean of school fee over total consumption expenditures in each month and each sub-district as well.

Results are reported in Tables 3.6 and 3.7. In Table 3.6 we see odds ratios, and in Table 3.7, we see MEs. In both Tables, the first three columns stand for poor households, and the last three columns stand for wealthy households.

As we can see, respectively in 2001, 2007 and 2011, the odds ratios (MEs) for poor households are equal to 1.3 (2.2%), 0.8 (-2.6%) and 1.5 (2.2%), and they are equal to 1.2 (1.1%), 0.7 (-2.5%) and 1.1 (0.2%) for wealthy households. The odds ratios and MEs on the time dummy are significant for poor households in all years, but for wealthy households, they are significant only in 2007.

First, as we see again, for both groups, odds ratios (MEs) on harvest time are more than one (positive) after harvest in normal conditions, while they are less than one (negative) during the shock. Therefore, our previous results are robust, and we conclude that the substitution effect dominates the income effect for both groups during the shock. Second, from the insignificancy (significancy) of the coefficients for wealthy (poor) households in normal conditions, we conclude that the decisions of wealthy (poor) households about sending children to work/school is not affected (is affected) by temporary changes of income in normal conditions, in other words, the decisions of the wealthy (poor) households about sending children to work/school are more stable (instable) in normal conditions. But, during the shock, both behave similarly. The MEs show that surprisingly the probability of putting children to work decreases by 2.5% after harvest.

Let's study the coefficients of other variables in Tables 3.5 and 3.6. The MEs and odds ratios of the wealth index for wealthy households are insignificant in all years; it indicates that the wealth of the wealthy households has no effect on the probability of sending children to work/school. But, the MEs for the poor households show that the probability falls by 3.9%, 13.4% and 1.3% when the wealth index increases by 1% respectively in 2001, 2007 and 2011.

With respect to the number of children below seven, we see that the more the number of children below seven, the more workload on children 7-14 years old. Children 7-14 years old bear responsibility for caring for their siblings. The effects, however, are not always significant.

About the number of adults above 15 years old in rural households, the results suggest that the more the number of adults, the less workload on children 7-14 years old. It means that adults take care of their little household members.

The coefficients on odds ratios of age of the child are more than one and highly significant in all years for both groups; as a child ages, the probability of being put to work increases. The probability of being put to work increases on average by about 0.9% for each one year that a child ages for both groups. This finding is consistent with the idea that once a child leaves school, he or she does not return; dropping out of school is cumulative over time. The MEs of the age variable for both groups are approximately constant for the three survey periods, which mean that the age profile of child labor did not change across the various survey years.

The ME for gender of the child shows that male children are more likely to be put to work than female children. But, the MEs and odds ratios are always insignificant except for poor households in 2007. The ME shows that poor male children are more likely to be put to work than poor female children by about 4.4% during the shock.

Odds ratios and MEs for the variable reflecting the education of the household head are highly significant in all years for both groups except for poor households in 2001. The MEs show that probability of being a child laborer decreases by about 1% (2.5%), 8.1% (4.7%) and 2.8% (1.7%) for poor (wealthy) households respectively in 2001, 2007 and 2011.Therefore, when head receives at least a primary certificate, the probability of his or her children becoming a child laborer rather than staying in school decreases, and this decrease is much larger during the crisis, and also it is larger for poor households.

The estimated MEs of gender of head show that male heads are more probable compared to female heads to put their children to work by about 2%, but the MEs are not always significant. The odd ratios and MEs on age of head are insignificant and very small, which may mean that age of head does not affect his/her decision about putting children to work even when they get elderly and even in crisis!

The coefficient on access to services is negative and significant in 2007 and 2011 but not in 2001. In other words, if a child is located in a place where infrastructure is better, it is less probable that the child is removed from school and put to work. This finding is consistent with lower travel and time costs of schooling in such areas, because schools and bus stops are closer. But, consider that the MEs are very small (about %0.5).

The MEs for the land holding variables are all negative and equal to 13.6% (4.9%), 7.2% (1.9%) and 2.5% (1.9%) for poor (wealthy) households, respectively, in 2001, 2007 and 2011. That is, as per capita land holding increases child labor decreases, but this effect shrank a lot over time, and it is larger for poor households than wealthy households.

If the probability of putting child to work versus per capital land holding is drawn, it will be seen that probability of being a child laborer decreases as per capita land holding increases, but there is a persistent upward bump in the relationship between child labor and landholding near the middle of the range of land per capita. Oryoie, Alwang and Tideman (2016) have explained theoretically and empirically about this pattern by a 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 per capita land holding.

Table 3.6. Odd ratios on school-aged child working. Logit models for poor and wealthy households.

	Poor Households			Wealthy Households		
	2001	**2007**	**2011**	**2001**	**2007**	**2011**
Harvest time	1.396**	0.777*	1.439**	1.233	0.741**	1.058
	(2.22)	(-1.90)	(2.40)	(1.06)	(-2.12)	(0.32)
Child Characteristics						
age	1.069**	1.114***	1.206***	1.125***	1.116***	1.382***
	(2.09)	(4.11)	(4.57)	(2.82)	(3.10)	(7.08)
Male	1.153	1.570***	1.189	1.017	1.222	1.269
	(1.17)	(4.28)	(1.33)	(0.13)	(1.59)	(1.55)
Household Characteristics						
Head education	0.924	0.349***	0.590***	0.599***	0.444***	0.551***
	(-0.35)	(-5.53)	(-2.94)	(-2.70)	(-4.61)	(-2.96)
Head male	0.971	1.294	1.469*	1.345	1.560**	0.951
	(-0.16)	(1.45)	(1.87)	(1.41)	(2.46)	(-0.26)
Head age	0.999	0.998	1.001	0.985	0.989	0.993
	(-0.17)	(-0.41)	(0.07)	(-1.63)	(-1.45)	(-0.70)
Males less than 7	0.908	1.011	1.135	1.149	0.954	1.215*
	(-1.14)	(0.12)	(1.28)	(1.57)	(-0.53)	(1.93)
Females less than 7	1.238**	1.152	1.183*	0.963	1.196**	1.029
	(2.13)	(1.60)	(1.71)	(-0.40)	(2.13)	(0.28)
Males 15-50	1.177**	0.968	0.959	0.963	0.987	0.974
	(2.22)	(-0.51)	(-0.51)	(-0.41)	(-0.17)	(-0.30)
Females 15-50	1.028	0.921	0.918	0.904	0.952	0.947
	(0.35)	(-1.14)	(-0.78)	(-1.25)	(-0.69)	(-0.57)
Males above 50	1.458*	1.200	1.124	1.549*	0.911	1.265
	(1.88)	(0.86)	(0.48)	(1.77)	(-0.49)	(1.00)
Females above 50	1.285	0.932	0.901	0.927	1.027	1.122
	(1.47)	(-0.46)	(-0.50)	(-0.38)	(0.17)	(0.64)
$\frac{\text{Land}}{\text{L}}$	0.020***	0.242***	0.345*	0.068**	0.548	0.188**
	(-3.58)	(-2.77)	(-1.81)	(-2.51)	(-1.07)	(-2.28)
$(\frac{\text{Land}}{\text{L}})^2$	144.045***	3.020**	3.055*	41.792**	1.582	6.159**
	(2.71)	(2.52)	(1.95)	(2.13)	(1.01)	(2.44)
$(\frac{\text{Land}}{\text{L}})^3$	0.181**	0.807**	0.765*	0.256*	0.917	0.673**
	(-2.08)	(-2.33)	(-1.85)	(-1.75)	(-0.94)	(-2.18)
Assets	0.574**	0.236***	0.760**	0.963	0.956	0.988
	(-1.98)	(-2.88)	(-2.39)	(-1.15)	(-1.50)	(-0.86)
School fee over	0.439	0.229	0.033**	0.065	9.372	1.730
total consumption.	(-0.42)	(-0.75)	(-2.10)	(-1.39)	(1.05)	(0.33)
Primary School	1.076***	1.002	1.002**	0.999	0.998	0.999
	(2.92)	(0.37)	(1.99)	(-0.22)	(-0.59)	(-1.04)
Secondary School	1.007	1.000	1.006	1.010	1.002	1.000
	(0.69)	(0.07)	(1.32)	(0.99)	(0.41)	(-0.23)
Constant	0.032***	0.071***	0.009***	0.024***	0.039***	0.001***
	(-6.54)	(-5.45)	(-7.55)	(-5.00)	(-4.72)	(-8.74)
Observations	4104	5904	7350	4542	6263	7325
R^2	0.05	0.07	0.05	0.05	0.05	0.09

*Denotes significance at 10%, **at 5% and ***at 1%. Numbers in parentheses are t statistics. Standard errors are clustered at the household level. Province fixed effects are controlled.

Table 3.7. Marginal effects on school-aged child working. Logit models for poor and wealthy households.

	Poor Households			Wealthy Households		
	2001	**2007**	**2011**	**2001**	**2007**	**2011**
Harvest time	0.026**	-0.026*	0.019**	0.011	-0.021**	0.002
	(2.35)	(-1.85)	(2.51)	(1.11)	(-2.05)	(0.33)
Child Characteristics						
age	0.005**	0.011***	0.011***	0.006***	0.007***	0.011***
	(2.09)	(4.14)	(4.72)	(2.81)	(3.10)	(6.59)
Male	0.012	0.045***	0.010	0.001	0.013	0.008
	(1.17)	(4.29)	(1.35)	(0.13)	(1.60)	(1.53)
Household Characteristics						
Head education	-0.006	-0.085***	-0.028***	-0.025***	-0.049***	-0.019***
	(-0.36)	(-6.80)	(-3.09)	(-2.89)	(-4.89)	(-3.02)
Head male	-0.002	0.026	0.021*	0.015	0.028**	-0.002
	(-0.16)	(1.46)	(1.86)	(1.48)	(2.55)	(-0.26)
Head age	-0.000	-0.000	0.000	-0.001	-0.001	-0.000
	(-0.17)	(-0.41)	(0.07)	(-1.64)	(-1.44)	(-0.70)
Males less than 7	-0.008	0.001	0.007	0.007	-0.003	0.006*
	(-1.13)	(0.12)	(1.28)	(1.57)	(-0.53)	(1.91)
Females less than 7	0.017**	0.014	0.010*	-0.002	0.012**	0.001
	(2.09)	(1.59)	(1.66)	(-0.40)	(2.12)	(0.28)
Males 15-50	0.013**	-0.003	-0.002	-0.002	-0.001	-0.001
	(2.19)	(-0.51)	(-0.51)	(-0.41)	(-0.17)	(-0.30)
Females 15-50	0.002	-0.008	-0.005	-0.005	-0.003	-0.002
	(0.35)	(-1.14)	(-0.78)	(-1.24)	(-0.69)	(-0.57)
Males above 50	0.031*	0.018	0.007	0.024*	-0.006	0.008
	(1.87)	(0.86)	(0.49)	(1.76)	(-0.49)	(1.00)
Females above 50	0.020	-0.007	-0.006	-0.004	0.002	0.004
	(1.48)	(-0.46)	(-0.50)	(-0.38)	(0.17)	(0.64)
$\frac{\text{Land}}{\text{L}}$	-0.130***	-0.070**	-0.020	-0.043**	-0.017	-0.015
	(-3.44)	(-2.52)	(-1.23)	(-2.02)	(-0.96)	(-1.39)
Assets	-0.045**	-0.144***	-0.016**	-0.002	-0.003	-0.000
	(-1.97)	(-2.85)	(-2.33)	(-1.16)	(-1.51)	(-0.86)
School fee over	-0.067	-0.147	-0.194**	-0.148	0.149	0.018
total consumption.	(-0.42)	(-0.75)	(-2.06)	(-1.38)	(1.05)	(0.33)
Primary School	0.006***	0.000	0.000**	-0.000	-0.000	-0.000
	(2.92)	(0.37)	(1.98)	(-0.22)	(-0.59)	(-1.04)
secondary School	0.001	0.000	0.000	0.001	0.000	-0.000
	(0.70)	(0.07)	(1.32)	(0.99)	(0.41)	(-0.23)
Observations	4104	5904	7350	4542	6263	7325

*Denotes significance at 10%, **at 5% and ***at 1%. Numbers in parentheses are t statistics. Standard errors are clustered at the household level. Province fixed effects are controlled.

3.5) Conclusion

We saw that Zimbabweans experienced an adverse shock in 2007-08, which caused rural households to get poorer. Shocks have opposite effects (income effect and substitution effect) on children's work/education, and theoretically it is not predictable which effect dominates. Therefore, we cannot predict theoretically whether child labor increases or decrease following these shocks.

Using three cross sectional surveys conducted in 2001, 2007-8 and 2010-11, we ran three different regressions in each year and controlled for regional unobservables and some institutional effects, and we saw that child labor increased after harvest before and after the shock, but it decreased after harvest during the shock.

We found that substitution effect dominates (human capital investments are countercyclical) in rural Zimbabwe. It means that policy makers wishing to reduce child labor could be happy during the crisis or other negative shocks in Zimbabwe. But, they should be worried during positive shocks since substitution effect dominates in Zimbabwe. That is, during positive shocks, opportunity cost of time of children increases, so children are put to work more.

Conclusion

In the first chapter, we calculate an asset index using multiple correspondence analysis (MCA) and use it to conduct inequality analysis in Zimbabwe. We show that the results are sensitive to the particular definition and construction of the dummy variables composing the asset base. Before running MCA, we must check the availability of assets, and it is important to check the signs and magnitudes of the estimated asset coordinates to ensure they are consistent with the local context. Some variables need to be modified or excluded. We explain how to decompose an asset-based index of relative inequality into between- and within-inequality, and we also develop a test of statistical significance of changes in the inequality index.

We show that inequality in whole of the country increased during the shock and after that decreased, but it did not return to its initial value. We also show that on average people got poorer in 2007, but they got wealthier after that in 2011, although not as much as 2001.

We see that between-inequality between urban and rural areas were twice as much as within inequality, and urban households were wealthier than rural households across all years.

We show that inequality between urban and rural increased during the shock, but it returned to its initial value after the shock. We see that during the shock, in rural areas inequality was the same as before the shock, but it increased after the shock. And in urban areas, inequality increased during the shock, but it returned to its initial value after the shock.

In the second chapter, we distinguish between the effect of productive and a non-productive wealth on child labor and discuss theoretically the relationship between child labor and the amount of productive wealth in the form of land. Since both children and land are factors of production for rural households, changes in one of them affect the productivity of the other. We show that the likelihood that a household puts its children to work generally falls as land holdings increase, with an upward bump near the middle of the range of land per capita. The upward bump observed in that 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.

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 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. Furthermore, we see in the empirical results that it is possible for the households who do not hold any land be either less or more likely to send their children to work than the households whose land holding is in an intermediate range. Therefore, policy makers should note that 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.

In the third chapter, we study the effect of the Zimbabwean hyperinflation in 2007-08 on child labor. It is explained that the income and substitution effects of shocks on child labor go in opposite directions and that it is not predictable from theory alone which effect dominates. Therefore we cannot predict theoretically whether child labor will increases or decrease following a shock.

Empirical results show that child labor increased after harvest before and after the shock, but it decreased after harvest during the shock. We find, in other words, that the substitution effect dominates (human capital investments are countercyclical) in rural Zimbabwe. This means that policy makers wishing to reduce child labor should be happy during the crisis or other negative shocks in Zimbabwe, but they should be worried during positive shocks, since it is in precisely these good times when the substitution effect dominates and children may be put to work. During positive shocks, the opportunity cost of the time of children increases considerably, so children are put to work more.

References

1. Asselin, L. M. (2009). *Analysis of multidimensional poverty: Theory and case studies* (Vol. 7). Springer Science & Business Media.
2. Bai, J. (2015). Separating the Income and Substitution Effects of Trade Liberalization on Schooling: Using Indian Tariff Reform as a Natural Experiment. *mimeo, Department of Economics, MIT.*
3. Banerjee A. V., & Newman A. F. (1993). Occupational Choice and the Process of Development. *Journal of Political Economy* 101(2), 274-298.
4. Bardhan, P., Bowles, S., & Gintis, H. (2000). Wealth inequality, wealth constraints and economic performance. *Handbook of income distribution*, *1*, 541-603.
5. Barro, R. J. (1991). Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, 106(2), 407-443.
6. Basu, K., Das, S., & Dutta, B. (2010). Child labor and household wealth: Theory and empirical evidence of an inverted-U. *Journal of development Economics*, *91*(1), 8-14.
7. Basu, K. (1999). Child labor: cause, consequence, and cure, with remarks on international labor standards. *Journal of Economic literature*, *37*(3), 1083-1119.
8. Basu, K., & Van, P. H. (1998). The economics of child labor. *American economic review*, 412-427.
9. Basu, K., & Tzannatos, Z. (2003). The Global Child Labor Problem: What do we know and what can we do?. *The world bank economic review*, *17*(2), 147-173.

10. Beegle, K., Dehejia, R., Gatti, R., & Krutikova, S. (2008). The Consequences of Child Labor: Evidence from Longitudinal Data in Rural Tanzania. *Policy Research Working Paper no. 4677, World Bank, Washington, DC.*

11. Benabou, R. (1994). Human capital, inequality, and growth: A local perspective. *European Economic Review, 38*(3-4), 817-826.

12. Bergstrom, Theodore. "Soldiers of Fortune?" In Essays *Essays in Honor of Kenneth J. Arrow: Volume 2, Equilibrium Analysis* (Vol. 2). Cambridge University Press.

13. Bhalotra, S., & Heady, C. (2003). Child farm labor: The wealth paradox. The World Bank Economic Review, 17(2), 197-227.

14. Brown, M. B., & Forsythe, A. B. (1974). Robust tests for the equality of variances. *Journal of the American Statistical Association*, 69(346), 364-367.

15. Bongaarts, J., & Casterline, J. (2013). Fertility Transition: Is sub-Saharan Africa Different?. *PoPulation and develoPment review*, *38*(s1), 153-168.

16. Booysen, F., Van Der Berg, S., Burger, R., Von Maltitz, M., & Du Rand, G. (2008). Using an asset index to assess trends in poverty in seven Sub-Saharan African countries. *World Development*, *36*(6), 1113-1130.

17. Brown, M. B., & Forsythe, A. B. (1974). Robust tests for the equality of variances. *Journal of the American Statistical Association*, *69*(346), 364-367.

18. Cogneau, D., & Jedwab, R. (2012). Commodity Price Shocks and Child Outcomes: The 1990 Cocoa Crisis in Côte d’Ivoire. *Economic Development and Cultural Change*, *60*(3), 507-534.

19. Cowell, F. (2011). *Measuring inequality*. Oxford University Press.

20. Diallo, Y., alex Etienne, & Mehran, F. (2013). *Global child labour trends 2008 to 2012*. ILO.

21. 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*.

22. Dumas, C. (2015). Shocks and child labor: the role of markets. In *SES Working paper*, 458.

23. Duryea, S., Lam, D., & Levison, D. (2007). Effects of economic shocks on children's employment and schooling in Brazil. *Journal of development economics*, *84*(1), 188-214.

24. Echevin, D. (2011). Vulnerability to asset-poverty in sub-Saharan Africa. Munich Personal RePEc Archive, MPRA Paper No. 35660.

25. Edmonds, E. V. (2007). Child labor. *Handbook of development economics*, *4*, 3607-3709.

26. Edmonds, E. V., & Turk, C. (2002). *Child labor in transition in Vietnam* (Vol. 2774). World Bank Publications.

27. Edmonds, E. (2005). Does child labor decline with improvements in economic status?. *Journal of Human Resources*, 40(1), 77–89.

28. Edmonds, E., & Pavcnik, N. (2005). Child Labour in the Global Economy. *Journal of Economic Perspectives*, 19(1), 199–220.

29. Edmonds, E. V., & Pavcnik, N. (2005). The effect of trade liberalization on child labor. *Journal of international Economics*, *65*(2), 401-419.

30. Emerson, P. M., & Souza, A. P. (2003). Is there a child labor trap? Intergenerational persistence of child labor in Brazil. *Economic Development and Cultural Change,* 51(2), 375–398.

31. Ersado, L. (2005). Child Labor and Schooling Decisions in Urban and Rural Areas: Comparative Evidence from Nepal, Peru, and Zimbabwe. *World Development,* 33(3), 455-480.

32. Filmer, D., & Pritchett, L. 1998. "Estimating wealth effects without income or expenditure data-or tears: Educational enrollment in India," *World Bank Policy Research Working Paper No. 1994. Washington, DC: Development Economics Research Group (DECRG), The World Bank.*

33. Filmer, D., & Pritchett, L. (1999). The effect of household wealth on educational attainment: evidence from 35 countries. *Population and development review*, *25*(1), 85-120.

34. Filmer, D., & Pritchett, L. H. (2001). Estimating wealth effects without expenditure data—or tears: an application to educational enrollments in states of India. *Demography*, *38*(1), 115-132.

35. Filmer, D., & Scott, K. (2012). Assessing asset indices. *Demography*, *49*(1), 359-392.

36. Foster, A. D., & Rosenzweig, M. R. (1994). A test for moral hazard in the labor market: contractual arrangements, effort, and health. *Review of Economics and Statistics,* 76(2), 213-227.

37. Foster, A. D., & Rosenzweig, M. R. (2004). Technological change and the distribution of schooling: evidence from green revolution India. *Journal of Development Economics* 74(1), 87–112.

38. Galor, O., & Zeira, J. (1993). Income distribution and macroeconomics. *The review of economic studies*, *60*(1), 35-52.

39. Garratt, R., & Marshall, J. M. (1994). Public finance of private goods: The case of college education. *Journal of Political Economy*, 566-582.

40. Greenacre, M., & Blasius, J. (Eds.). (2006). *Multiple correspondence analysis and related methods*. CRC press.

41. Guarcello, L., Mealli, F., & Rosati, F. (2002). Household Vulnerability and Child Labour, The Effect of Shocks, Credit Rationing and Insurance, UCW paper Florence. *Avalable at: http://www. ucw-project. org/pdf/publications/standard_CL_and_Vulnerability. pdf (Retrieved on 13th November 2007)*.

42. Hanke, H., & Kwok, A. K. F., (2009). On the measurement of Zimbabwe's hyperinflation. *The Cato Journal* 29 (2), 353–364.

43. International Labour Organization (ILO). (1996). Child Labour Today: Facts and Figures. Geneva.

44. Jacoby, H. G. (1993). Shadow wages and peasant family labor supply: an econometric application to the Peruvian Sierra. *Review of Economic Studies*, 60 (4), 903–921.

45. Jacoby, H. G., & Skoufias, E. (1997). Risk, Financial Markets, and Human Capital in a Developing Country. *The Review of Economic Studies*, 64(3), 311-335.

46. Jayaraj, D., & Subramanian, S. (2007). Out of School and (Probably) in Work: Child Labour and Capability Deprivation in India. *Journal of South Asian Development* 2(2), 177–226.

47. Jensen, R. (2000). Agricultural volatility and investments in children. *The American Economic Review*, *90*(2), 399-404.

48. Kambhampati, U. S., & Rajan, R. (2006). Economic Growth: A Panacea for Child Labor? *World Development*, 34(3), 426-445.

49. Kolenikov, S., & Angeles, G. (2009). Socioeconomic status measurement with discrete proxy variables: Is principal component analysis a reliable answer?. *Review of Income and Wealth*, *55*(1), 128-165.

50. Kruger, D. I. (2007). Coffee Production Effects on Child Labor and Schooling in Rural Brazil. *Journal of Development Economics*, 82(2), 448-463.

51. Larochelle, C., Alwang, J., & Taruvinga, N., (2014). Inter-temporal changes in well-being during conditions of hyperinflation: Evidence from Zimbabwe. *Journal of African Economies*, 23(2), 225-256.

52. Le Roux, B., & Rouanet, H. (2010). *Multiple correspondence analysis* (Vol. 163). Sage.

53. Lima, L. R., Mesquita, S., & Wanamaker, M. (2015). Child labor and the wealth paradox: The role of altruistic parents. *Economics Letters*, *130*, 80-82.

54. Mabaye, M, (2005). Land reform in Zimbabwe: An Examination of Past & Present Policy, Shortcomings & Successes and Recommendations for Improvement, Harare, Zimbabwe.

55. Marongwe, N. (2002). *Conflicts over Land and other Natural*. by: ZERO Regional Environment Organisation.

56. McKenzie, D. J. (2005). Measuring inequality with asset indicators. *Journal of Population Economics*, *18*(2), 229-260.

57. Menon, N. (2005). Why Might Credit Used to Finance Investments Increase Child Labor?. In *Brandeis University Working Paper*.

58. Moyo, S. (2011). Three decades of agrarian reform in Zimbabwe. *Journal of Peasant Studies*, *38*(3), 493-531.

59. Olson Lanjouw, J., & Lanjouw, P. (2001). How to compare apples and oranges: Poverty measurement based on different definitions of consumption. *Review of Income and Wealth*, *47*(1), 25-42.

60. Oryoie, A. R., Tideman, N., & Alwang, J. (2016). "Inequality analysis using multiple correspondence analysis: Empirical evidence from Zimbabwe" *mimeo, Department of Economics, Virginia Tech.*

61. Oryoie, A. R., Alwang, J., & Tideman, N. (2016). Child labor and household land holding: Theory and empirical evidence from Zimbabwe. *Working Paper, Department of Economics, Virginia Tech.*

62. Pauly, M. V. (1967). Mixed public and private financing of education: Efficiency and feasibility. *The American Economic Review*, *57*(1), 120-130.

63. Ray, R. (2000). Child labor, child schooling and their interaction with adult labor: empirical evidence for Peru and Pakistan. *World Bank Economic Review* 14(2), 347–367.

64. Richardson, C. J. (2013). Zimbabwe: Why is One of the World's Least-Free Economies Growing so Fast?. *Cato Institute Policy Analysis*, (722).

65. Rosenzweig, M. R., & Wolpin, K. I. (1985). Specific experience, household structure, and intergenerational transfers: farm family land and labor arrangements in developing countries. *The Quarterly Journal of Economics*, 961-987.

66. Sahn, D. E., & Stifel, D. C. (2000). Poverty comparisons over time and across countries in Africa. *World development*, *28*(12), 2123-2155.

67. Schady, N. R. (2004). Do macroeconomic crises always slow human capital accumulation?. *The World Bank Economic Review*, *18*(2), 131-154.

68. Snedecor, G. W., & Cochran, W. G. (1989). Statistical methods, 8thEdn. *Ames: Iowa State Univ. Press Iowa*.

69. Swain, R. B. (2001). Demand, Segmentation and Rationing in the Rural Credit Markets of Puri. Ph.D. diss., Economic Studies 54, Uppsala University, Department of Economics, Sweden.

70. The Guardian, UK "Land redistribution is not robbery, but a necessity" 'Land redistribution is not robbery, but a necessity.

71. Thomas, D., Beegle, K., Frankenberg, E., Sikoki, B., Strauss, J., & Teruel, G. (2004). Education in a Crisis. Journal of Development Economics, 74(1), 53-85.

72. Vincent, V., Thomas, R. G., & Staples, R. R. (1960). *An agricultural survey of Southern Rhodesia. Part 1. Agro-ecological survey.*

73. Ward, P. (2014). Measuring the level and inequality of wealth: an application to China. *Review of Income and Wealth*, *60*(4), 613-635.

74. Weir, S. (2011). Parental Attitudes and Demand for Schooling in Ethiopia. *Journal of African Economies*, 20(1), 90-110.

75. Yu, D. (2008). The Comparability of Income and Expenditure Surveys 1995, 2000, and 2005/2006. *Draft paper. Department of Economics, University of Stellenbosch*.

Appendix A

Inflation in Zimbabwe

Table A.1. Zimbabwe's Hyperinflation

Date	Month-over-month inflation rate(%)	Year-over-year inflation rate(%)
March2007	50.54	2,200.20
April2007	100.70	3,713.90
May2007	55.40	4,530.00
June2007	86.20	7,251.10
July2007	31.60	7,634.80
August2007	11.80	6,592.80
September2007	38.70	7,982.10
October2007	135.62	14,840.65
November2007	131.42	26,470.78
December2007	240.06	66,212.30
January2008	120.83	100,580.16
February2008	125.86	164,900.29
March2008	281.29	417,823.13
April2008	212.54	650,599.00
May2008	433.40	2,233,713.43
June2008	839.30	11,268,758.90
July2008	2,600.24	231,150,888.87
August2008	3,190.00	9,690,000,000.00
September2008	12,400.00	471,000,000,000.00
October2008	690,000,000.00	3,840,000,000,000,000,000.00
14November2008	79,600,000,000.00	89,700,000,000,000,000,000,000.00

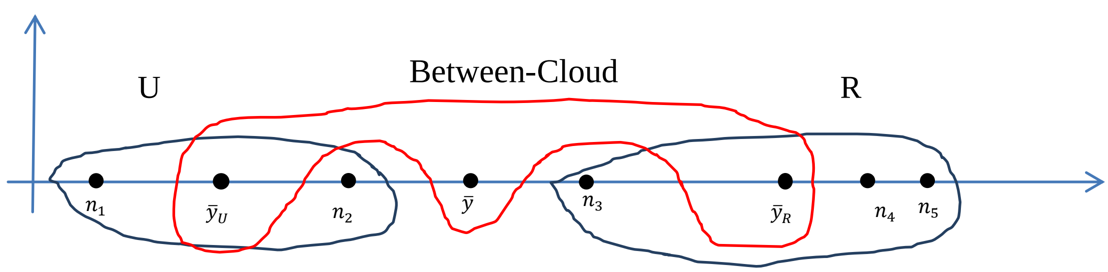
Used with permission of Steve H. Hanke. Source: Hanke, Steve H., and Alex K. F. Kwok. "On the Measurement of Zimbabwe's Hyperinflation." *Cato Journal* 29.2 (2009): 353-64.

Appendix B:

Decomposing Variance

Using an example it is explained how to calculate between and within variances. Suppose we have a cloud of five individuals (points), and we divide it into two groups of U= $\{n_1, n_2\}$ and R= $\{n_3, n_4, n_5\}$. The two groups are disjoint, and the cloud of 5 individuals is the union of these groups. These groups are presented by blue lines in Figure B1.

Figure B.1. A typical decomposition of a cloud into two sub-clouds.



$\bar{y}_R$ is mean of group R, $\bar{y}_U$ is mean of group U and $\bar{y}$ is mean of cloud. The two mean points $\bar{y}_R$ and $\bar{y}_U$ define a new cloud called the between-cloud illustrated by the red line in Figure B1. The between-cloud is a weighted cloud, in other words, each point in the between-cloud has a specific weight equal to the number of the points in the group it comes from divided by the total number of points. In our example, weight of $\bar{y}_R$ is $\frac{3}{5}$ and weight of $\bar{y}_U$ is $\frac{2}{5}$. The mean point of the between-cloud is a weighted mean point, which coincides with $\bar{y}_U$; that is, $\bar{y} = \frac{3}{5}\bar{y}_R + \frac{2}{5}\bar{y}_U$.

Now we can calculate between variance, which is in fact the variance of the between-cloud. It is the weighted mean of the squared distances of the mean points of the groups from the mean point of the cloud. This variance is called between-variance and is denoted by $\mathrm{V_{between}}$:

$$\mathrm{V_{between}} = \frac{3}{5}(\bar{y}_R - \bar{y})^2 + \frac{2}{5}(\bar{y}_U - \bar{y})^2 \tag{B.1}$$

In order to find within variance, we show the variance of each group as below:

$$\mathrm{V_R} = \frac{1}{3}\left((y_{n_3} - \bar{y})^2 + (y_{n_4} - \bar{y})^2 + (y_{n_5} - \bar{y})^2\right) - (\bar{y}_R - \bar{y})^2 \tag{B.2}$$

$$\mathrm{V_U} = \frac{1}{2}\left((y_{n_1} - \bar{y})^2 + (y_{n_2} - \bar{y})^2\right) - (\bar{y}_U - \bar{y})^2 \tag{B.3}$$

Multiply (B.2) by $n_R = 3$ and (B.3) by $n_U = 2$, then divide both equations by the total number of individuals $n_R + n_U = 5$, add (B.2) to (B.3) and rearrange the summation to get:

$$\begin{aligned} &\frac{3}{5}\mathrm{V_R} + \frac{2}{5}\mathrm{V_U} \\ &= \underbrace{\frac{1}{5}\left((y_{n_1} - \bar{y})^2 + (y_{n_2} - \bar{y})^2 + (y_{n_3} - \bar{y})^2 + (y_{n_4} - \bar{y})^2 + (y_{n_5} - \bar{y})^2\right)}_{\mathrm{V_{cloud}}} \\ &- \underbrace{\left(\frac{3}{5}(\bar{y}_R - \bar{y})^2 + \frac{2}{5}(\bar{y}_U - \bar{y})^2\right)}_{\mathrm{V_{between}}} \end{aligned} \tag{B.4}$$

The first term on the right hand side of (B.4) is the variance of the cloud of the individuals and the second term is the between variance, therefore the left hand side is within variance, so we have:

$$\mathrm{V_{within}} = \frac{3}{5}\mathrm{V_R} + \frac{2}{5}\mathrm{V_U} \tag{B.5}$$

By the same way, It can be shown that if we divide the cloud of individuals into G groups, then the within and between variance will be:

$$V_{within} = \sum_{g=1}^{G} \frac{n_g}{N} V_g \quad ; \quad V_g = \frac{\sum_{i=1}^{n_g} (y_i - \bar{y}_i)^2}{n_g} \tag{B.6}$$

$$V_{between} = \sum_{g=1}^{G} \frac{n_g}{N} (\bar{y}_g - \bar{y})^2 \quad ; \; \bar{y}_g = \frac{\sum_{i=1}^{n_g} y_i}{n_g} \text{ and } \bar{y} = \sum_{g=1}^{G} \frac{n_g}{N} \bar{y}_g \tag{B.7}$$

Where n_g is the number of individuals in group g, $N = \sum_{g=1}^{G} n_g$ is the total number of the individuals, V_g is the variance of the group g and $\bar{y}_g$ is the mean point of the group g.

Appendix C

Logit Model

In this appendix we explain a little bit about latent utility index models. Maximization of expected utility representation implies that two choices *w* and *s* involve comparison of expected utilities U_w (utility of sending a child to work) and U_s (utility of sending a child to school). But, we do not see the utilities and all variables that affect the preferences. Suppose y_i^* denotes a latent variable which cannot be observed by researcher (we can interpret it as the utility difference between $y_i = 1$ and $y_i = 0$, that is, the utility difference between sending a child to work and school, which is equal to $U_w - U_s$). Suppose y_i^* depends on x_i. Then we can write:

$$y_i^* = x_i'\beta + \varepsilon_i \tag{C.1}$$

Where $E(\varepsilon_i) = 0$. We can only see y_i. y_i is set equal to 1 if y_i^* is positive and 0 otherwise, that is:

$$y_i = \begin{cases} 1 & \text{if } \ y_i^* > 0 \\ 0 & \text{if } \ y_i^* \leq 0 \end{cases} \tag{C.2}$$

Suppose x_i and y_i are both *i.i.d.*, and $\varepsilon_i | x_i \sim N(0,1)$. Now the probability that $y_i = 1$ can be derived from the latent variable:

$$\begin{aligned} Pr(y_i = 1 \,|x_i) &= \Pr(y_i^* > 0 \,|x_i\,) = \Pr(x_i'\beta + \varepsilon_i > 0 \,|x_i) \\ &= \Pr(\varepsilon_i > -x_i'\beta \,|x_i) = 1 - F(-x_i'\beta) = F(x_i'\beta) \end{aligned} \tag{C.3}$$

Where $F(z) = e^z/(1 + e^z)$ for a logit model.

The marginal effects of a change in x_{ik} on the expected value of the observed variable y_i is:

$$\frac{\partial E(y_i|x_i)}{\partial x_{ik}} = \frac{e^{x_i'\beta}}{(1 + e^{x_i'\beta})^2}\beta_k \tag{C.4}$$

Ali Reza Oryoie.

September/2016.

End.